OIPE
MAY 22 2006
PATENT & TRADEMARK OFFICE

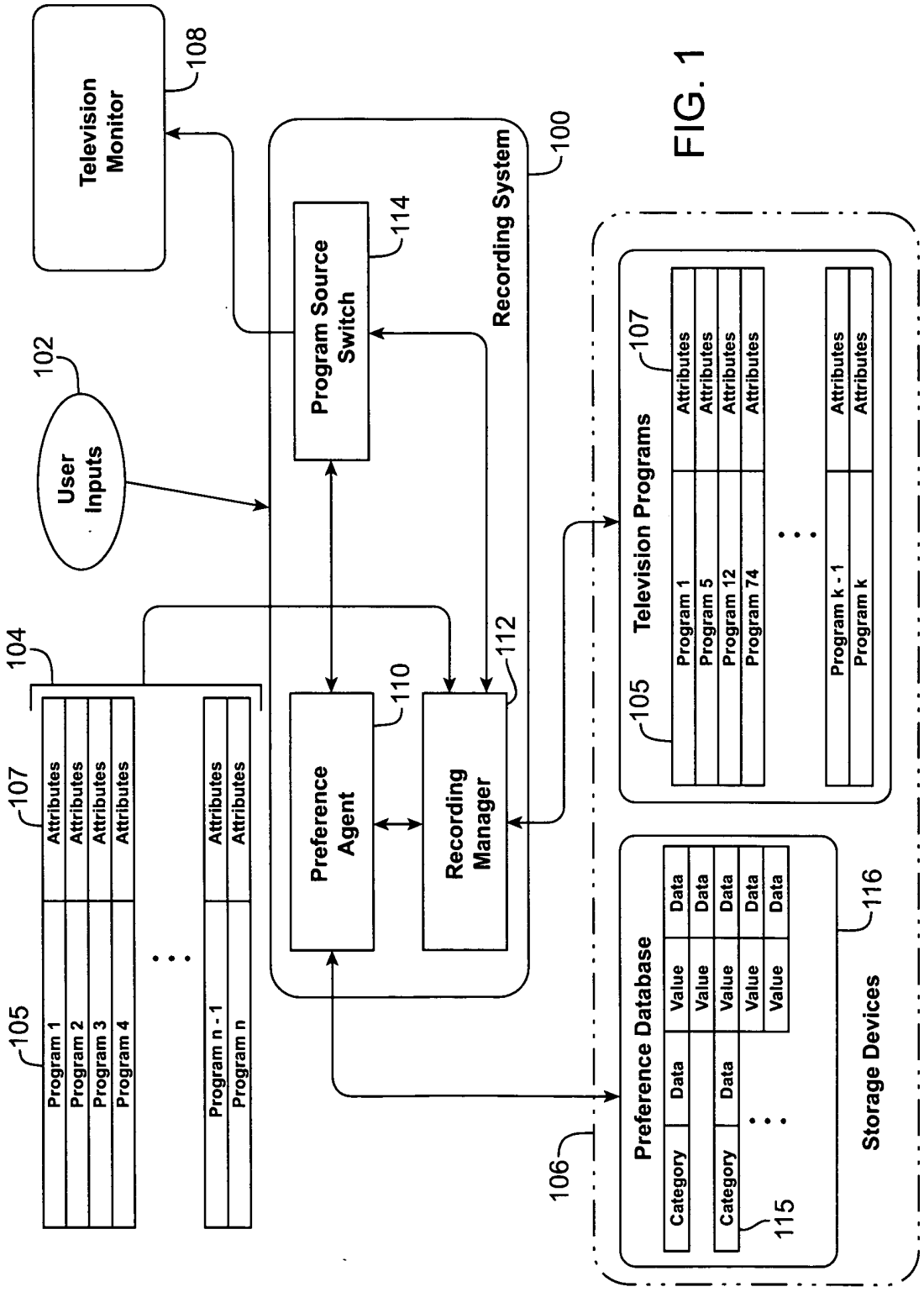


FIG. 1

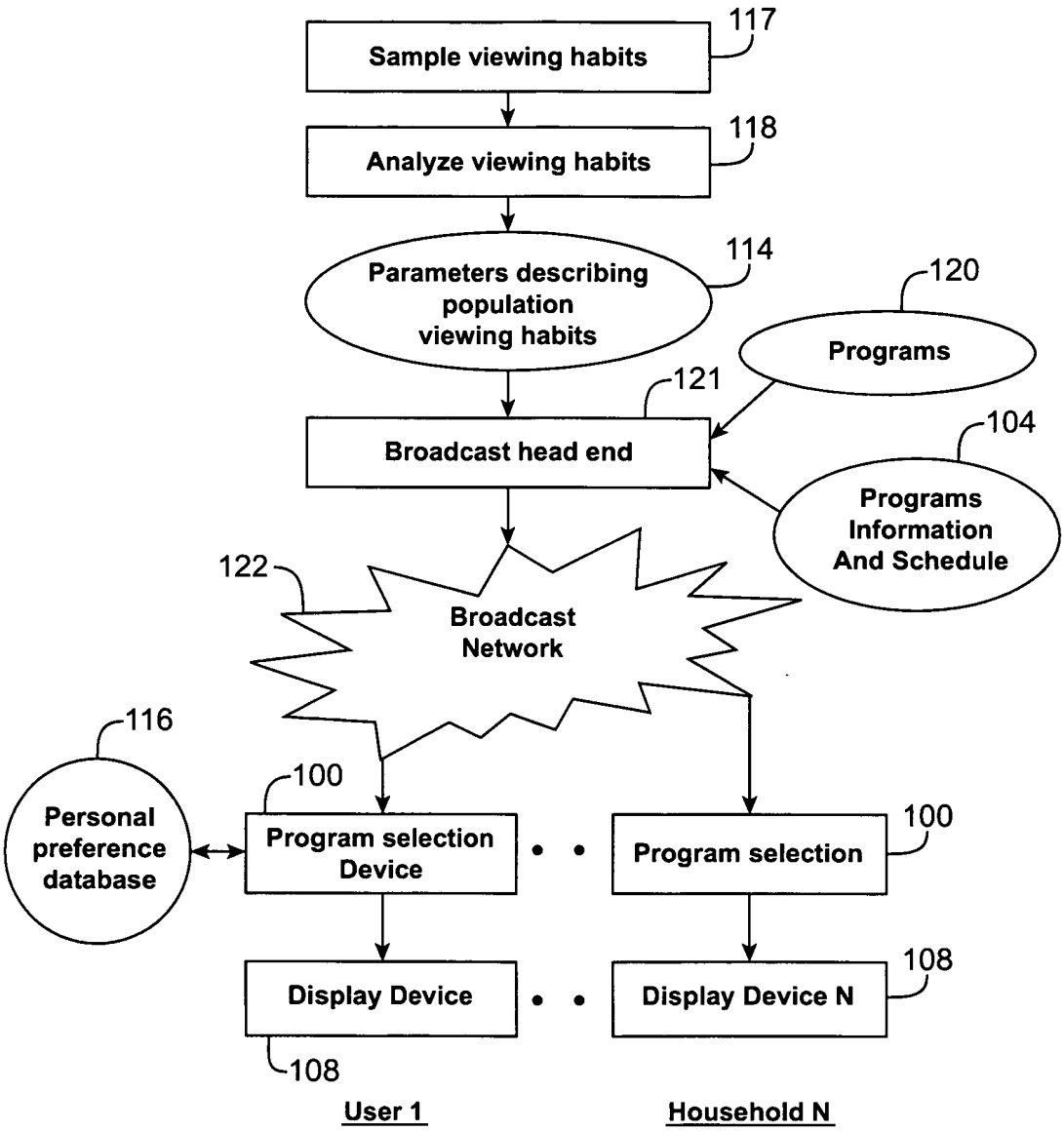

Sample viewing habits
117
Analyze viewing habits
118
Parameters describing population viewing habits
114
Programs
120
121
Broadcast head end
104
Programs Information And Schedule
122
Broadcast Network
116
Personal preference database
100
Program selection Device
Program selection
100
Display Device
Display Device N
108
108
User 1
Household N

FIG. 2

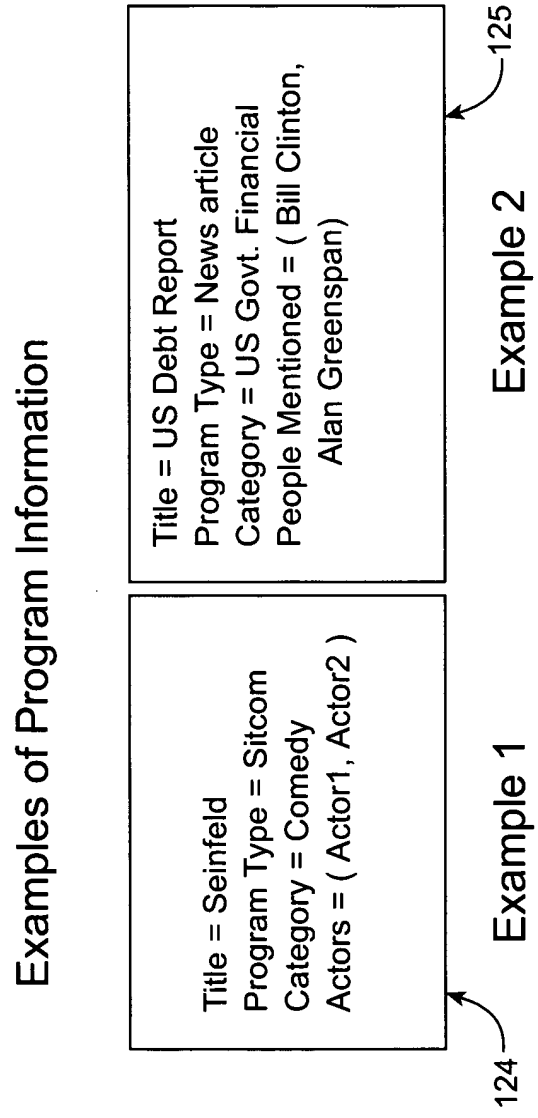

Examples of Program Information
Title = Seinfeld
Program Type = Sitcom
Category = Comedy
Actors = (Actor1, Actor2)
Example 1
124
Title = US Debt Report
Program Type = News article
Category = US Govt. Financial
People Mentioned = (Bill Clinton,
Alan Greenspan)
Example 2
125

FIG. 3

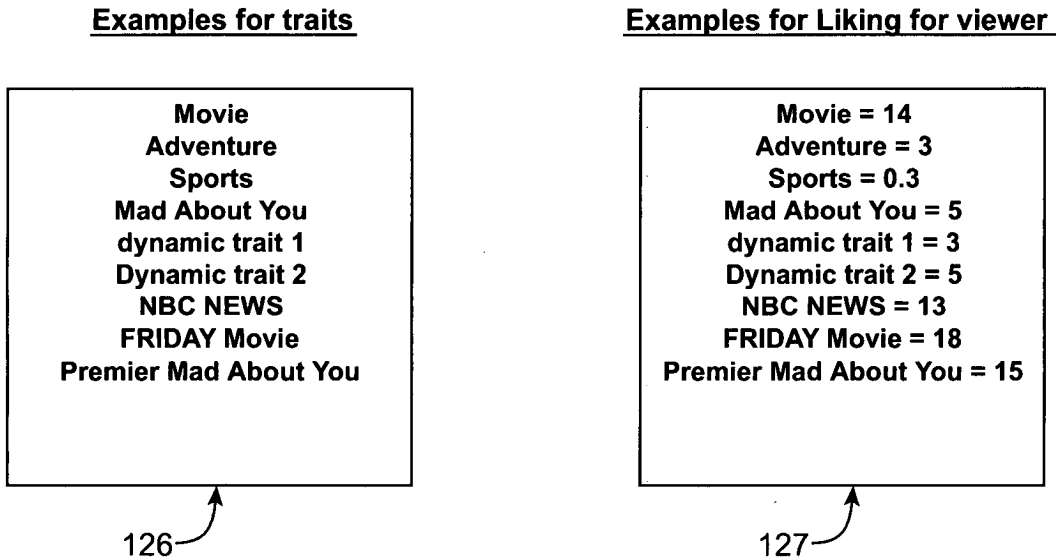

Examples for traits
Movie
Adventure
Sports
Mad About You
dynamic trait 1
Dynamic trait 2
NBC NEWS
FRIDAY Movie
Premier Mad About You
126
Examples for Liking for viewer N
Movie = 14
Adventure = 3
Sports = 0.3
Mad About You = 5
dynamic trait 1 = 3
Dynamic trait 2 = 5
NBC NEWS = 13
FRIDAY Movie = 18
Premier Mad About You = 15
127

FIG. 4

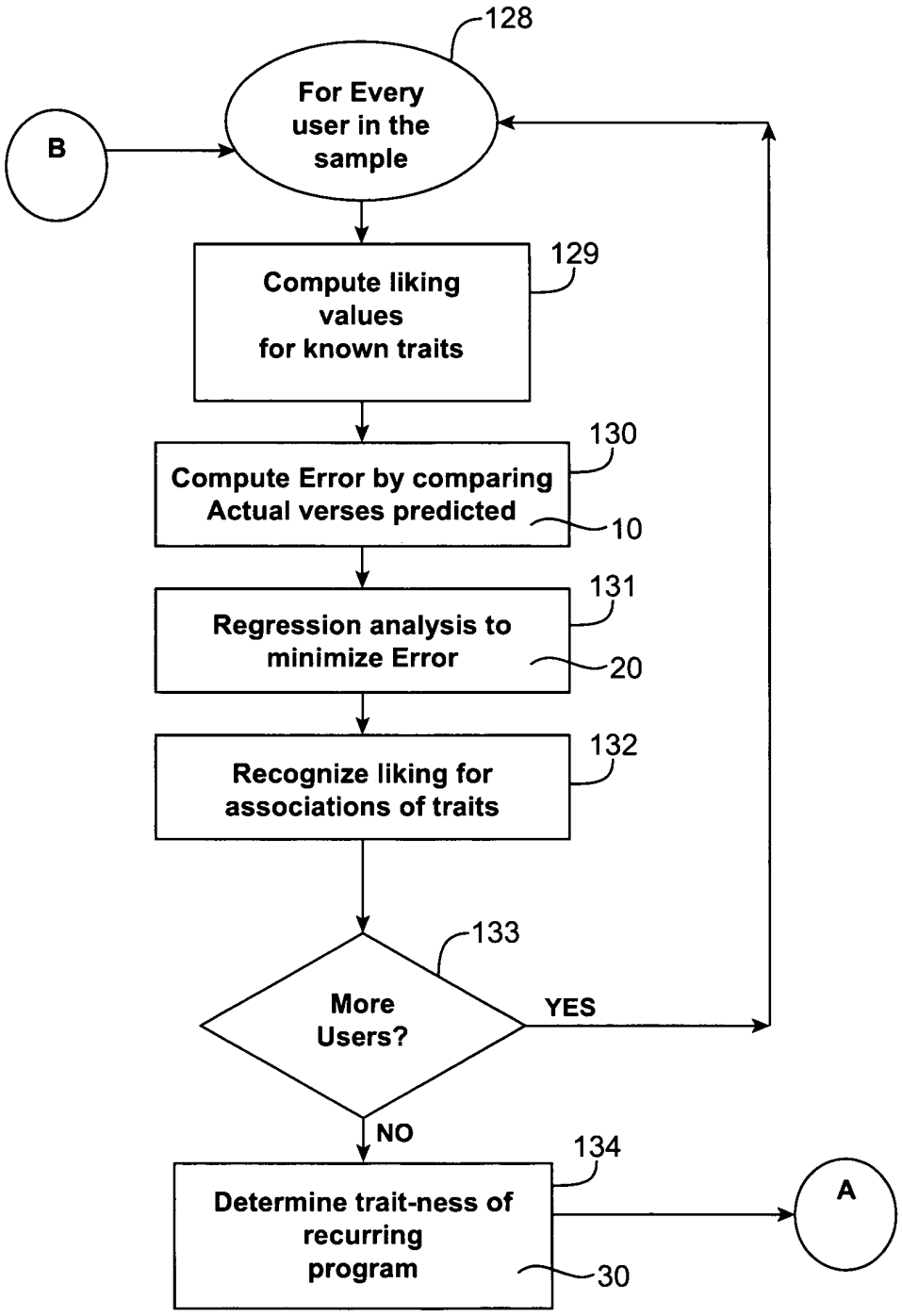

128
For Every user in the sample
B
129
Compute liking values for known traits
130
Compute Error by comparing Actual verses predicted
10
131
Regression analysis to minimize Error
20
132
Recognize liking for associations of traits
133
More Users?
YES
NO
134
Determine trait-ness of recurring program
30
A

FIG. 5(a)

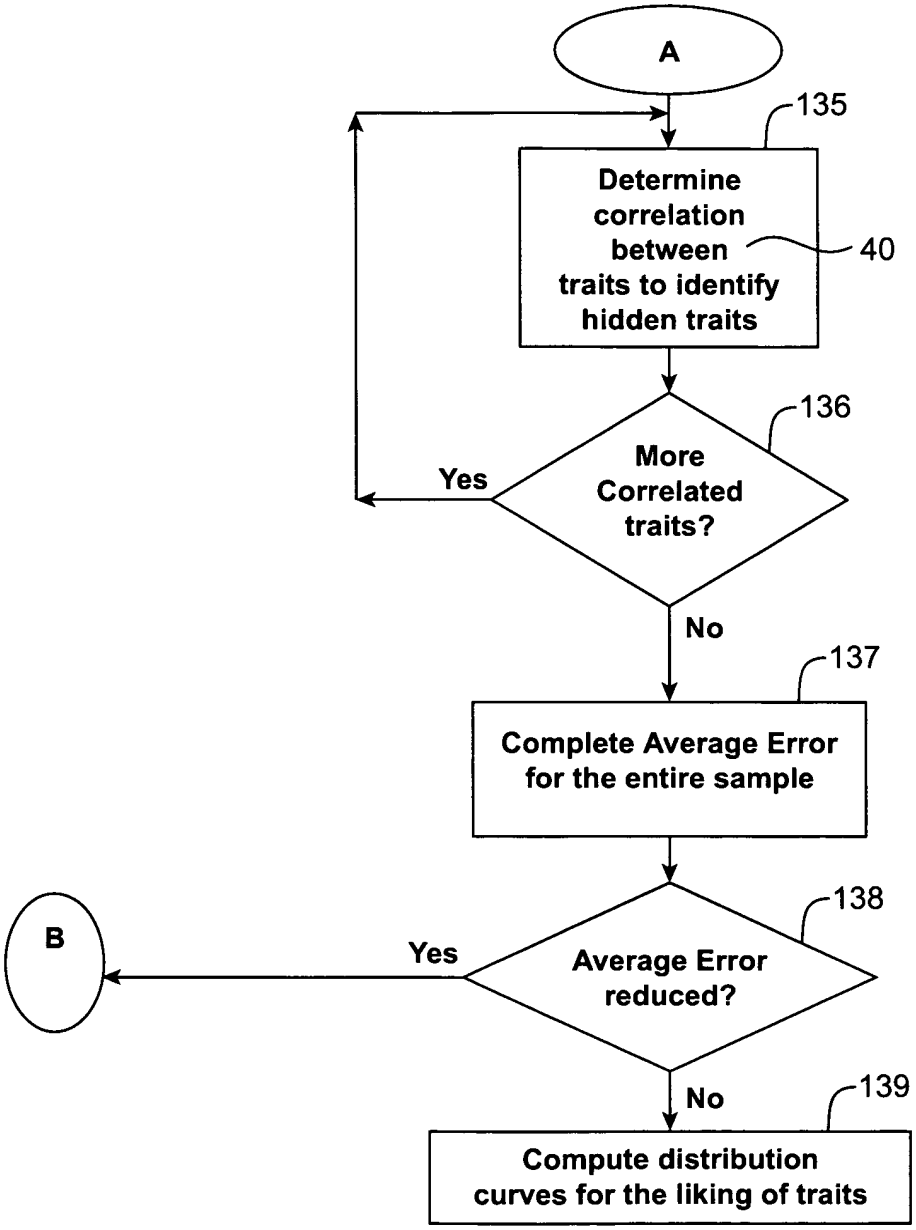

A
135
Determine correlation between traits to identify hidden traits
40
136
More Correlated traits?
Yes
No
137
Complete Average Error for the entire sample
138
Average Error reduced?
Yes
B
No
139
Compute distribution curves for the liking of traits

FIG. (5b)

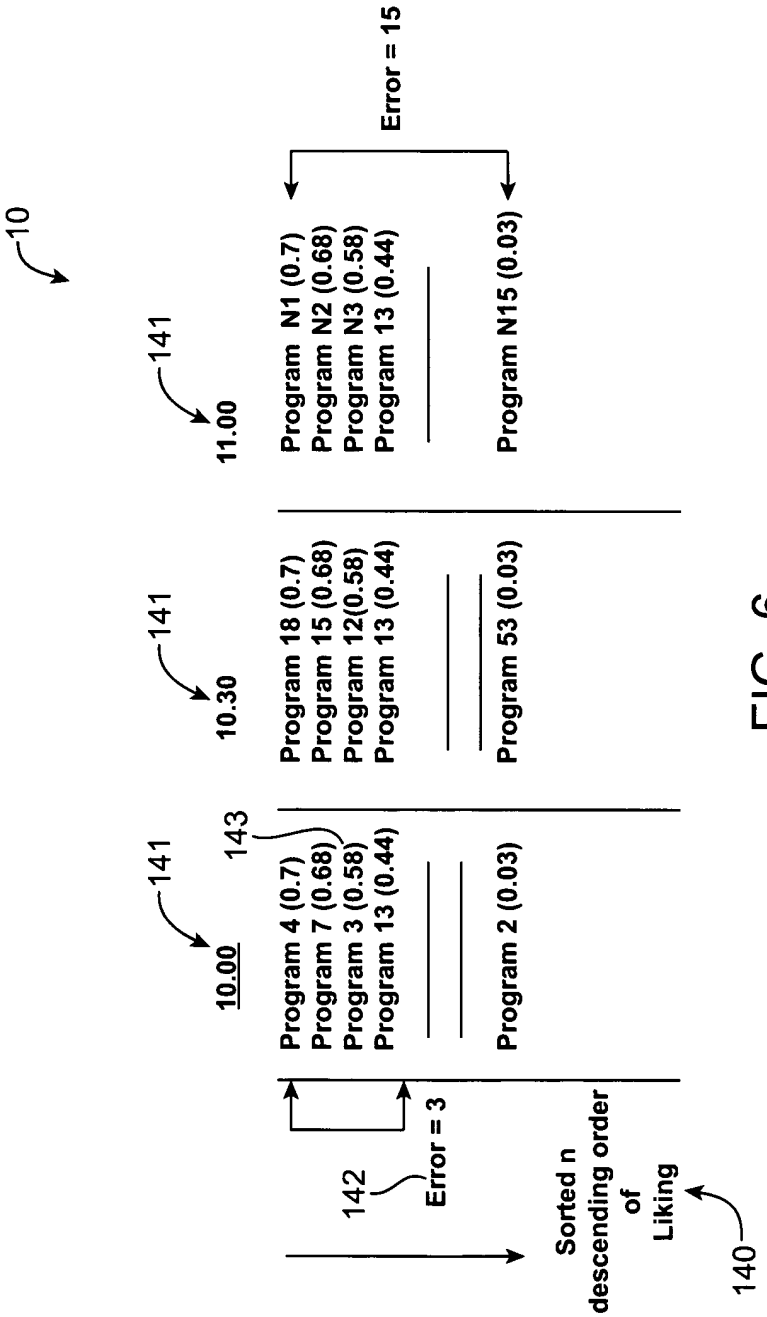

10
141
11.00
Program N1 (0.7)
Program N2 (0.68)
Program N3 (0.58)
Program 13 (0.44)
Program N15 (0.03)
Error = 15
141
10.30
Program 18 (0.7)
Program 15 (0.68)
Program 12(0.58)
Program 13 (0.44)
Program 53 (0.03)
141
10.00
143
Program 4 (0.7)
Program 7 (0.68)
Program 3 (0.58)
Program 13 (0.44)
Program 2 (0.03)
142
Error = 3
Sorted n descending order of Liking
140

FIG. 6

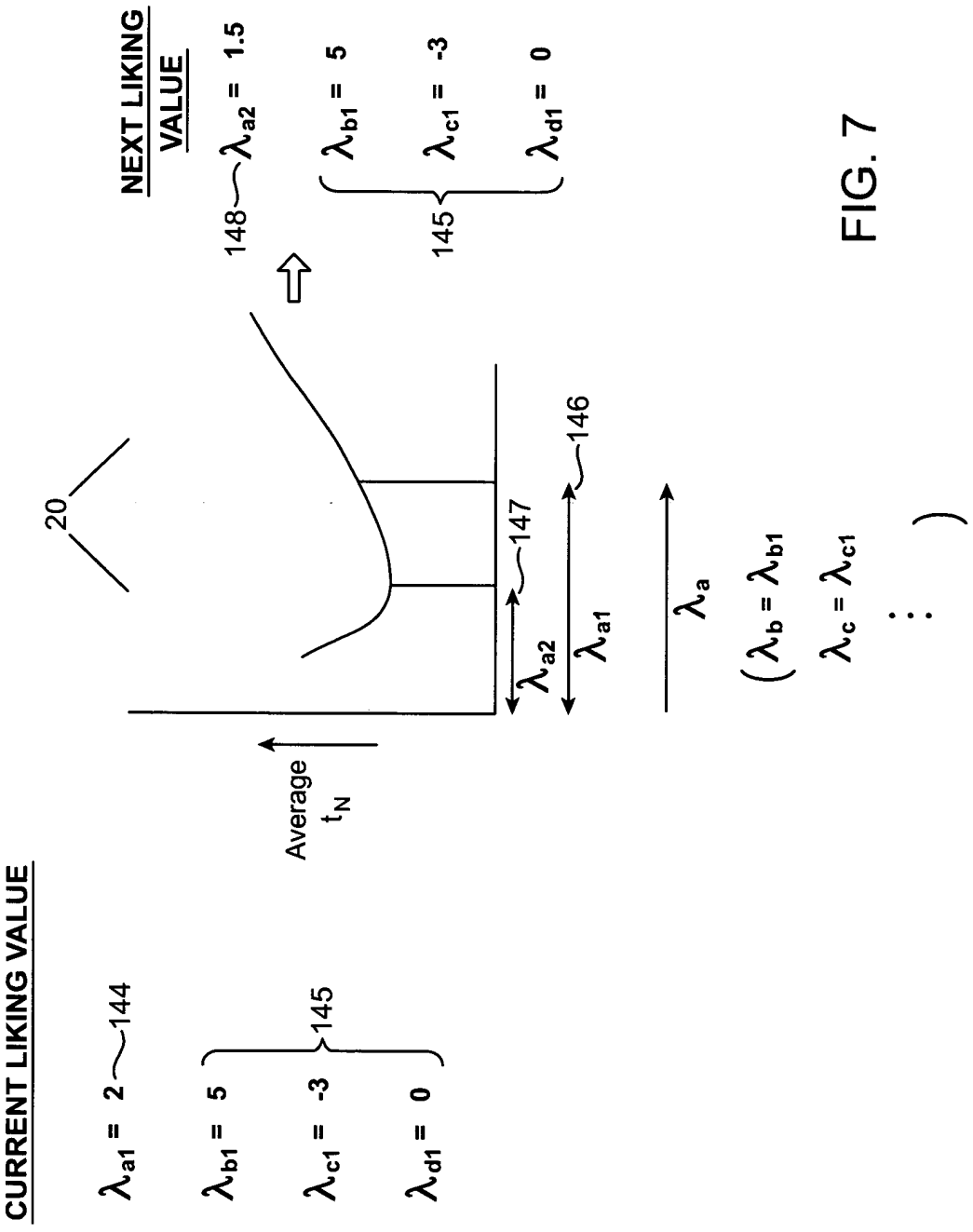
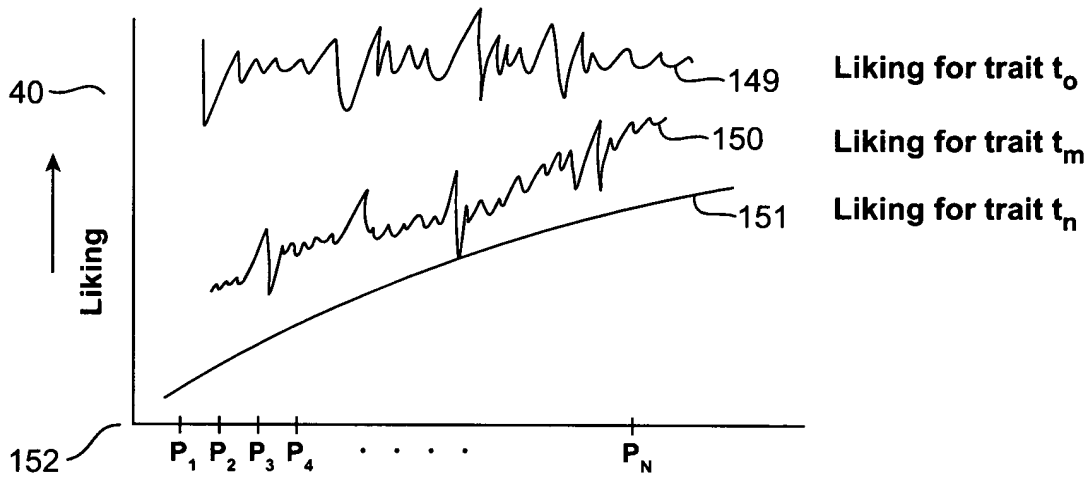

CURRENT LIKING VALUE
λ_{a1} = 2
144
λ_{b1} = 5
λ_{c1} = -3
λ_{d1} = 0
145
Average t_N
20
147
146
λ_{a2}
λ_{a1}
λ_a
($\lambda_b = \lambda_{b1}$
$\lambda_c = \lambda_{c1}$
: :)
NEXT LIKING VALUE
148
λ_{a2} = 1.5
λ_{b1} = 5
λ_{c1} = -3
λ_{d1} = 0
145

FIG. 7

RECOGNIZING HIDDEN TRAITS IN PROGRAMS



t_m & t_n are correlated

$\Rightarrow$ t_m can be expressed as $t_m = t_x + t_{m'}$

t_n can be expressed as $t_n = Ct_x + t_{m'}$

FIG. 8

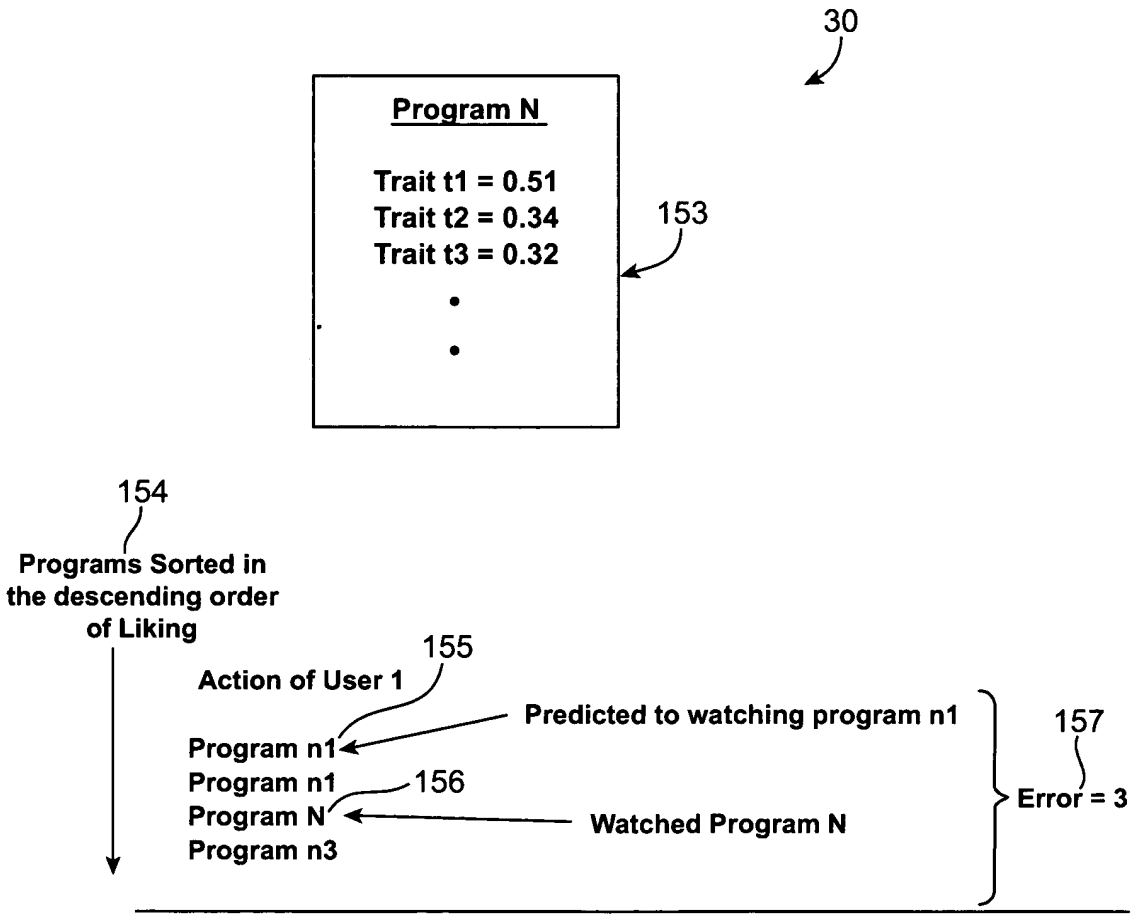

Computing Traitness of a trait is a program
30
Program N
Trait t1 = 0.51
Trait t2 = 0.34
Trait t3 = 0.32
153
154
Programs Sorted in the descending order of Liking
155
Action of User 1
Predicted to watching program n1
Program n1
Program n1
156
Program N
Watched Program N
Program n3
157
Error = 3

FIG. 9(a)

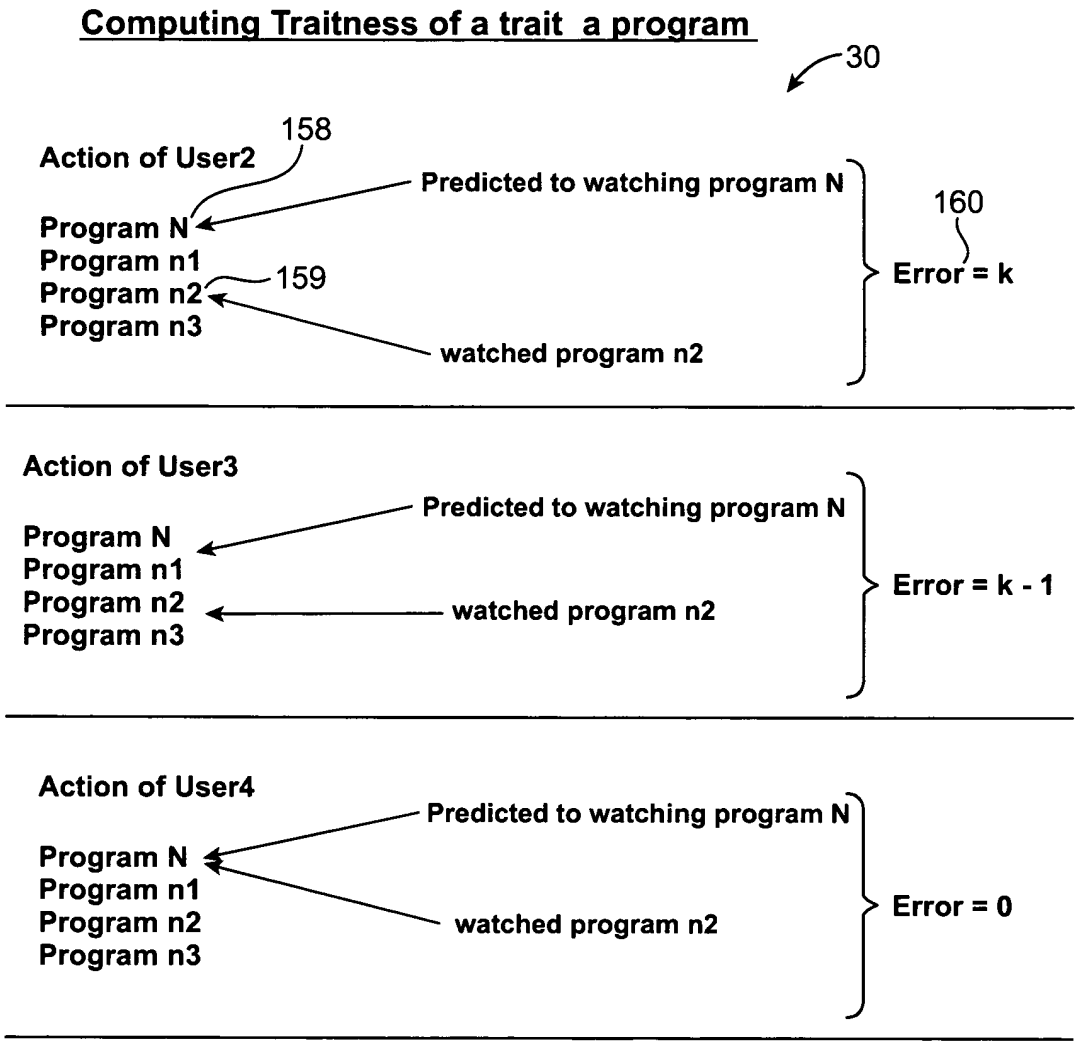

Computing Traitness of a trait a program
30
158
Action of User2
Predicted to watching program N
Program N
Program n1
Program n2
Program n3
159
watched program n2
160
Error = k
Action of User3
Predicted to watching program N
Program N
Program n1
Program n2
Program n3
watched program n2
Error = k - 1
Action of User4
Predicted to watching program N
Program N
Program n1
Program n2
Program n3
watched program n2
Error = 0

FIG. 9(b)

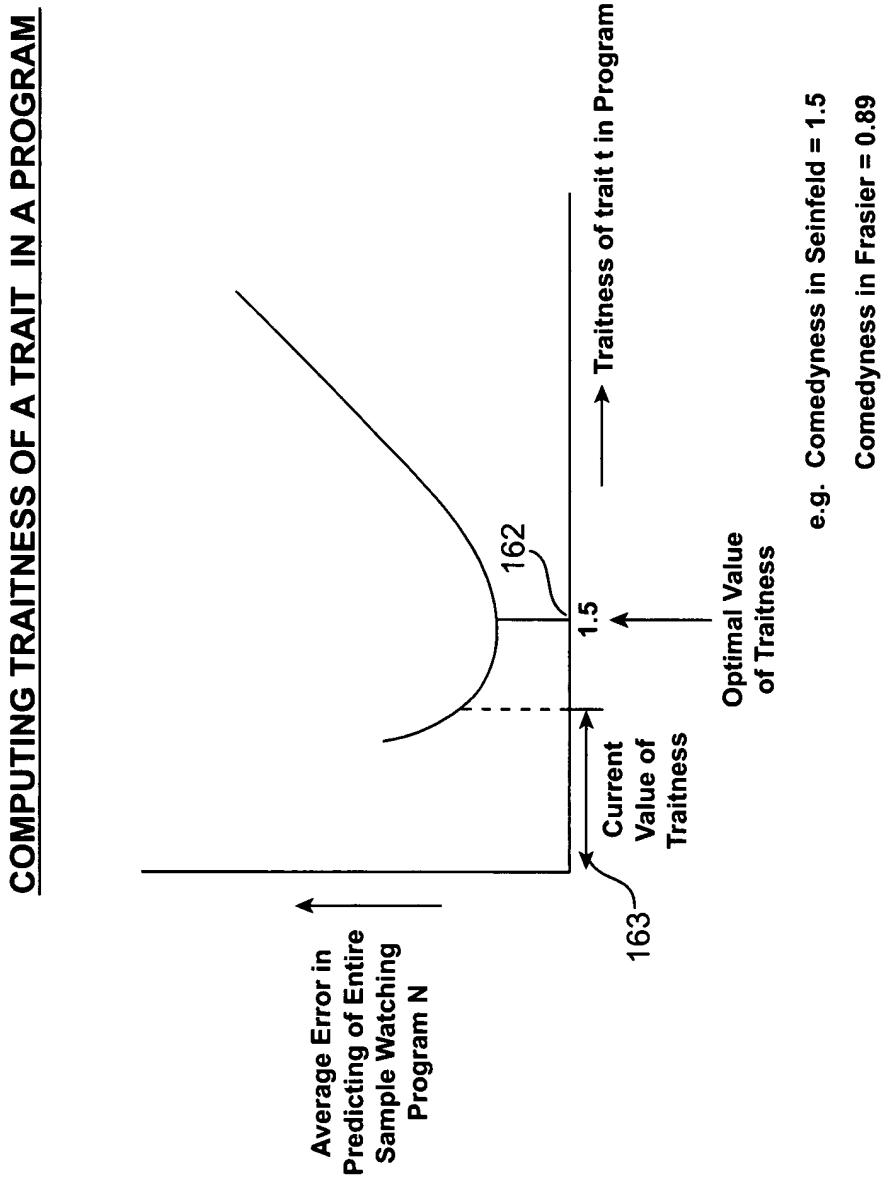

COMPUTING TRAITNESS OF A TRAIT IN A PROGRAM
Average Error in Predicting of Entire Sample Watching Program N
Traitness of trait t in Program N
162
1.5
Optimal Value of Traitness
Current Value of Traitness
163
e.g. Comedyness in Seinfeld = 1.5
Comedyness in Frasier = 0.89

FIG. 9(c)

Example for Liking Distribution Record format

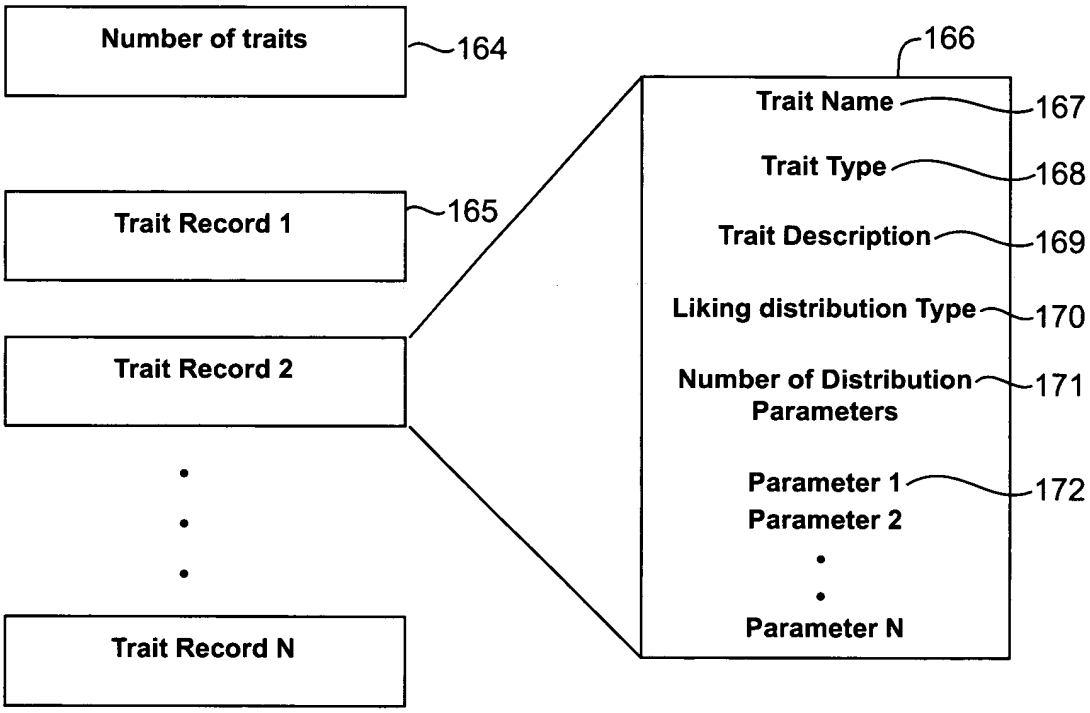


FIG. 10

Some Sample Values For Fields in trait Record

Trait type	Trait Description
Static	(NBC, "NEWS"),
dynamic	SUBSTRING("CIA") IN DESC.
Association	TITLE
Generated	

Distribution	Distribution Parameters
Normal	Mean = 13, Deviation = 2
Exponential	
Defined type 1	
Defined type 2	

FIG. 11

Example for Traitness of recurring Programs

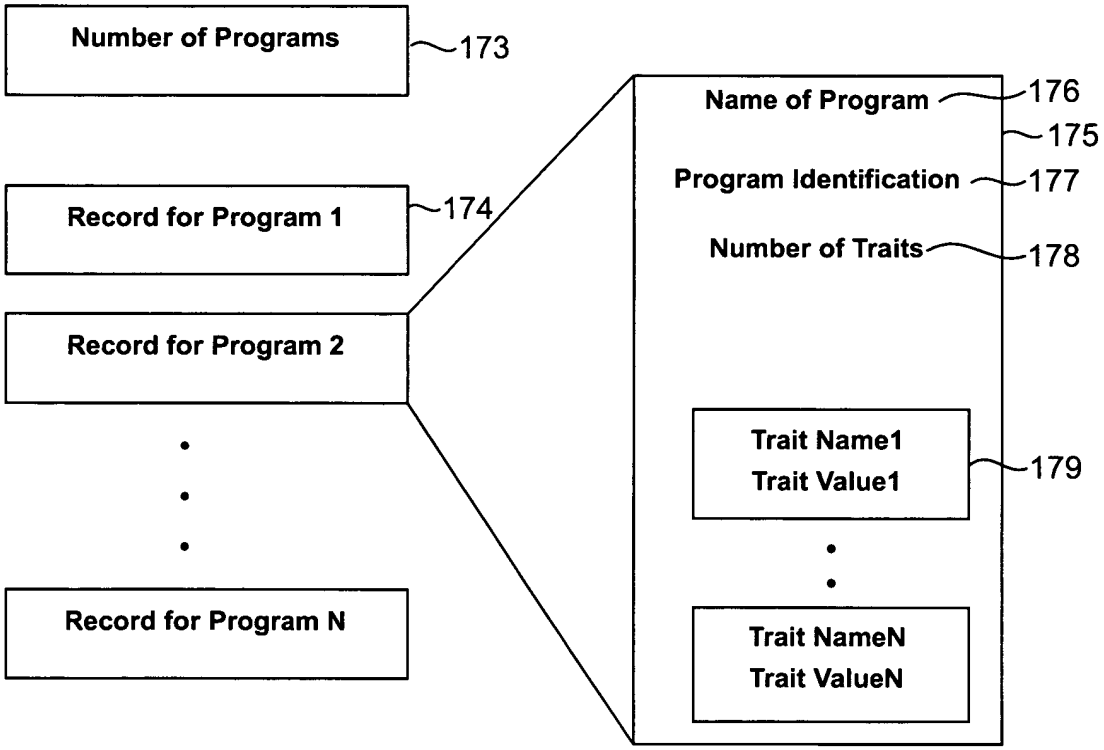


FIG. 12

Example For Broadcsting traitness as a part of EPG Data

Program Info
Seinfeld,
NBC,
Comedy = 0.07
sitcom,
Dynamic trait 1 = 0.1

•
•

Actor = Seinfeld

FIG. 13

Example for Selection Record

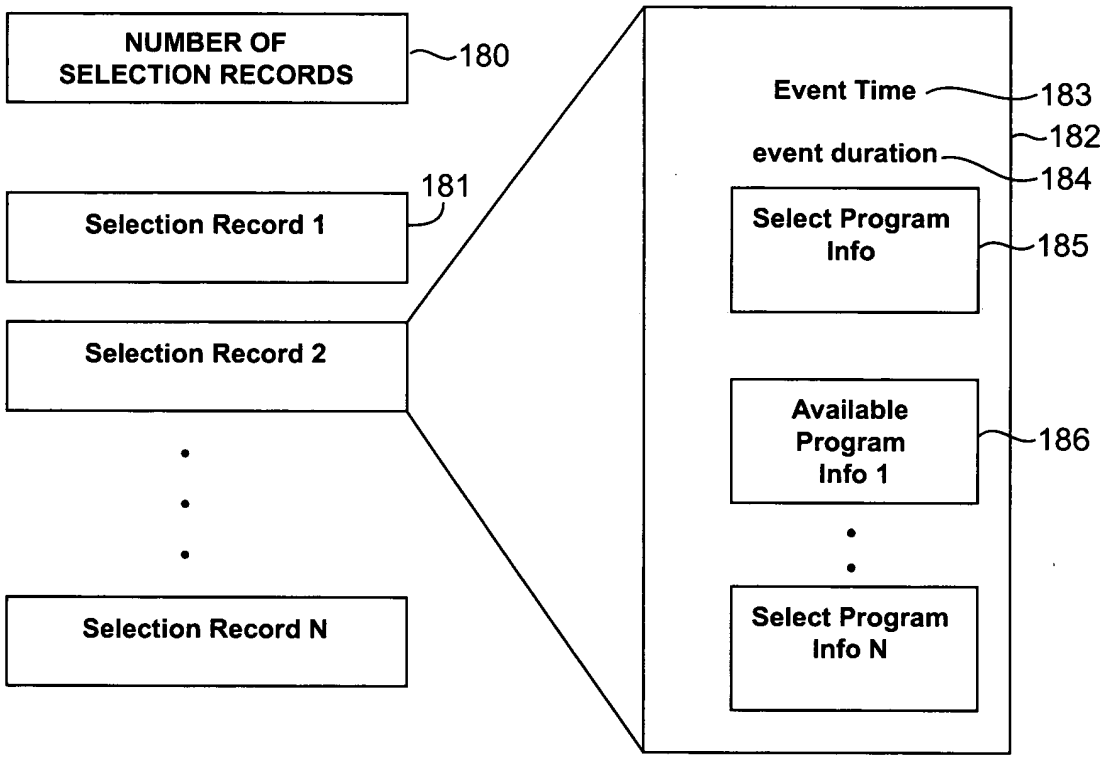


FIG. 14

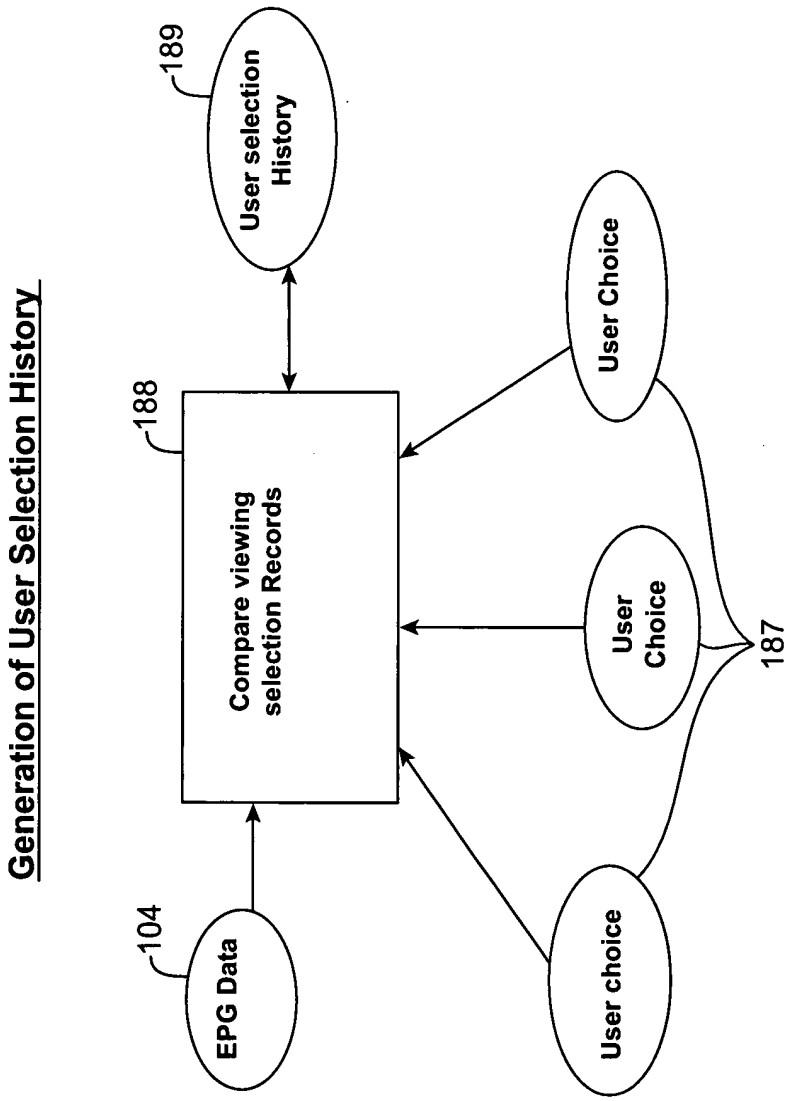

Generation of User Selection History
189
User selection History
188
Compare viewing selection Records
104
EPG Data
User Choice
User Choice
User choice
187

FIG. 15

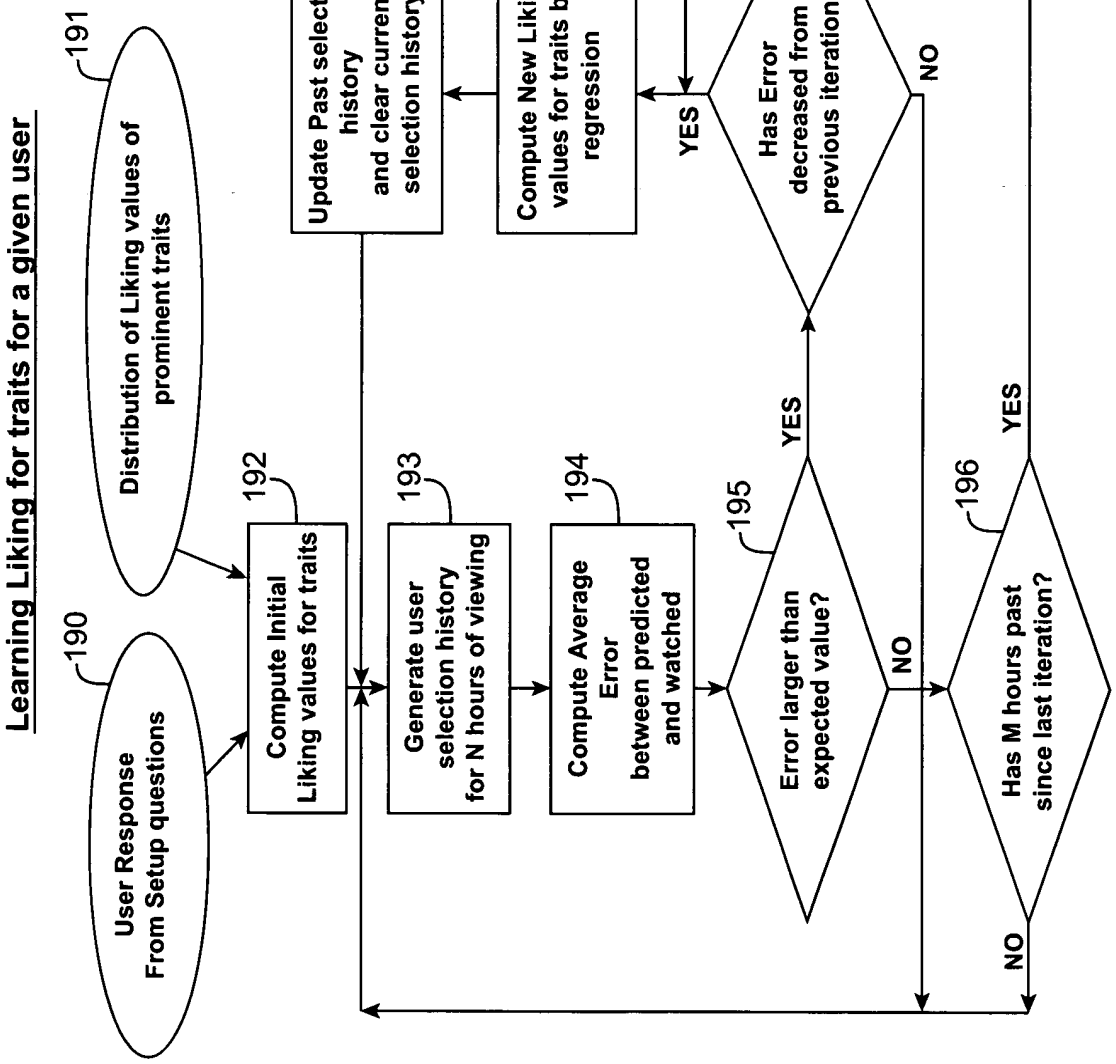

Learning Liking for traits for a given user
User Response From Setup questions
190
Distribution of Liking values of prominent traits
191
Compute Initial Liking values for traits
192
Generate user selection history for N hours of viewing
193
Compute Average Error between predicted and watched
194
Error larger than expected value?
195
YES
NO
Has M hours past since last iteration?
196
YES
NO
Has Error decreased from previous iteration?
197
YES
NO
Compute New Liking values for traits by regression
198
Update Past selection history and clear current selection history
197

FIG. 16

Computing Relevance

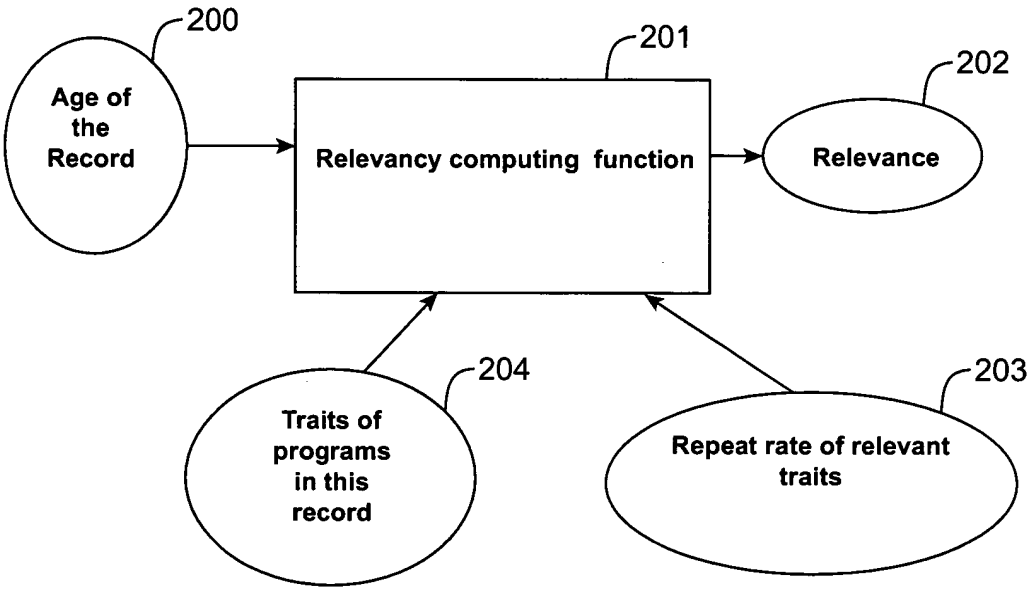


FIG. 17(a)

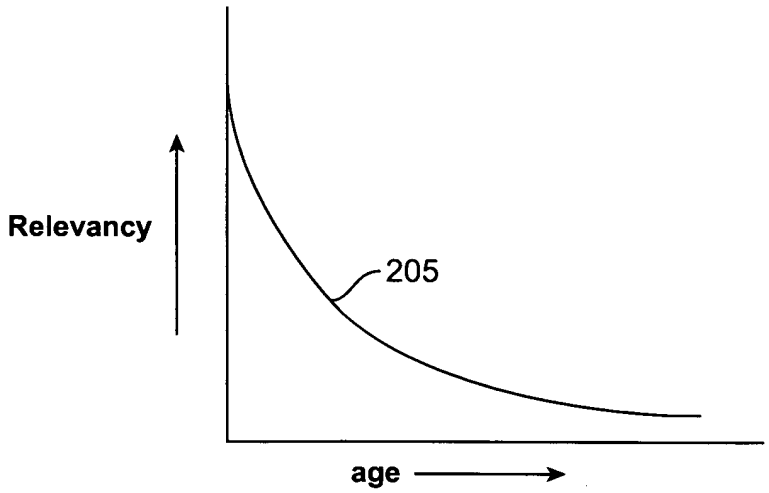


FIG. 17(b)

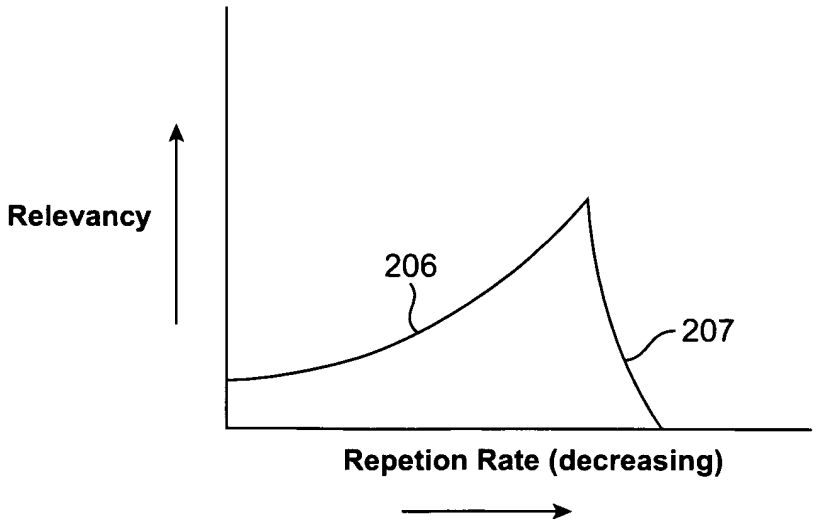


FIG. 17(c)

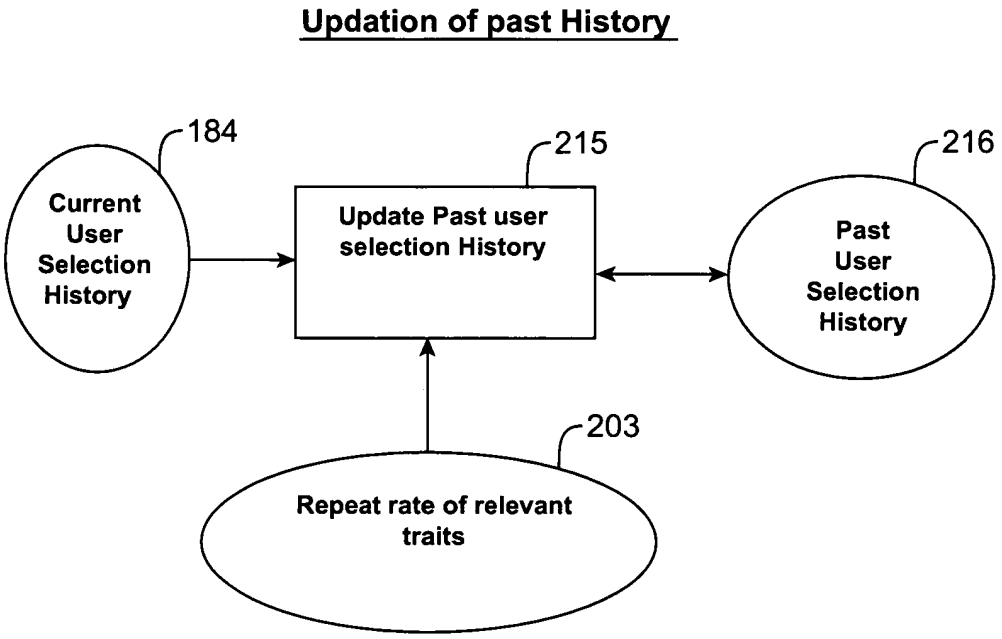

Updation of past History
184
Current User Selection History
215
Update Past user selection History
216
Past User Selection History
203
Repeat rate of relevant traits

FIG. 18(a)

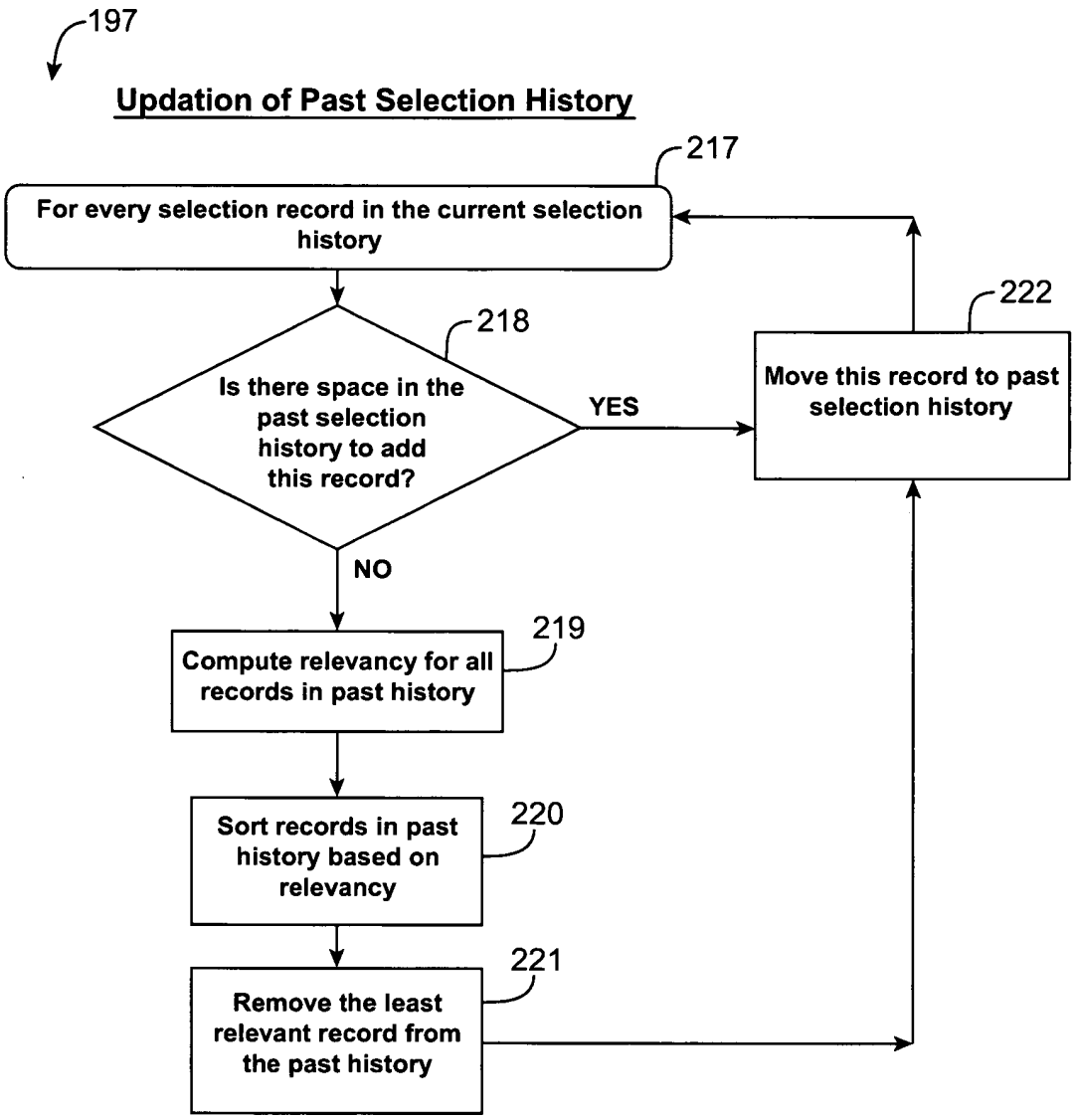

197
Updation of Past Selection History
217
For every selection record in the current selection history
218
Is there space in the past selection history to add this record?
YES
222
Move this record to past selection history
NO
219
Compute relevancy for all records in past history
220
Sort records in past history based on relevancy
221
Remove the least relevant record from the past history

FIG. 18(b)

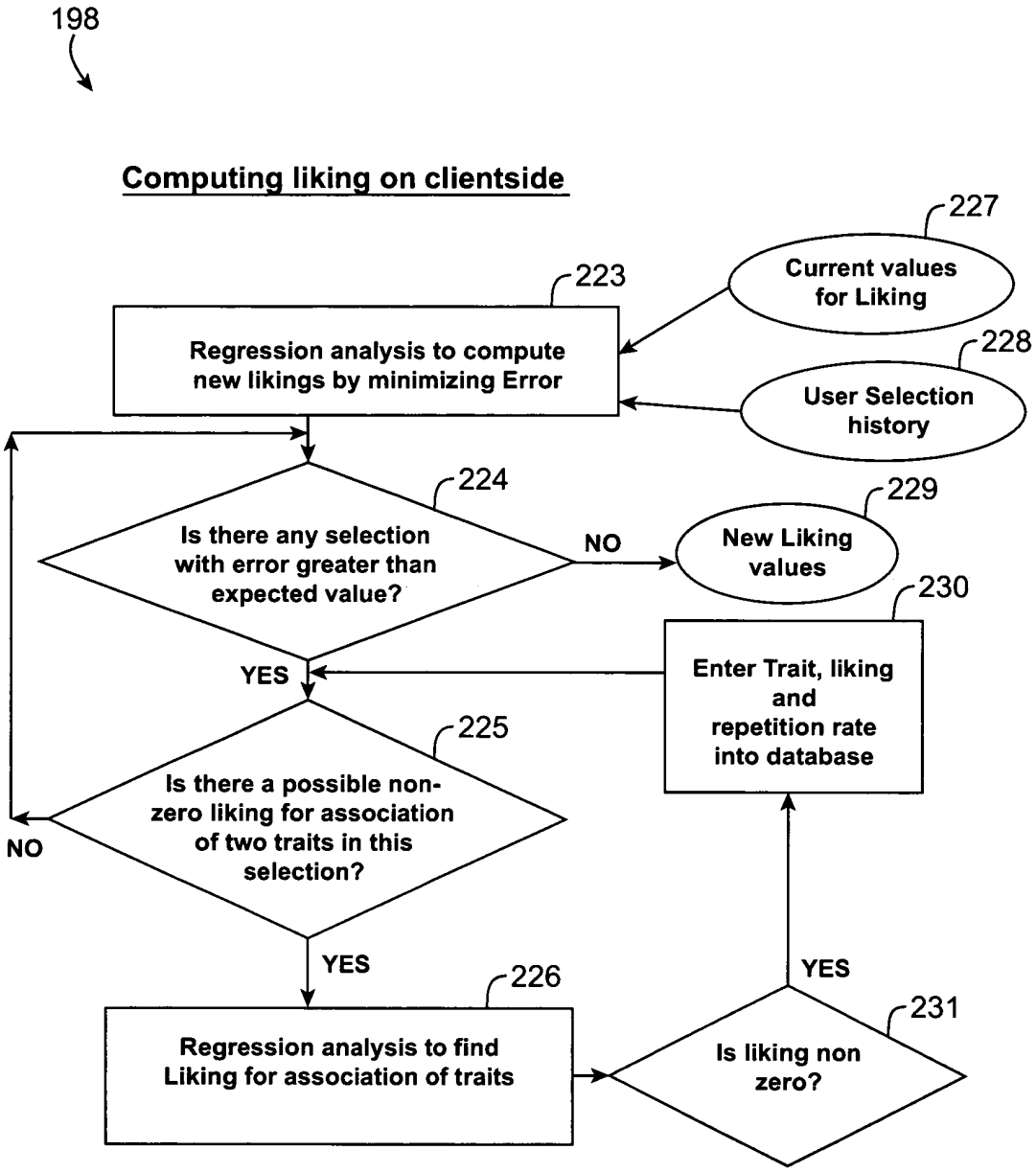

198
Computing liking on clientside
227
Current values for Liking
223
Regression analysis to compute new likings by minimizing Error
228
User Selection history
224
Is there any selection with error greater than expected value?
NO
229
New Liking values
230
Enter Trait, liking and repetition rate into database
YES
225
Is there a possible non-zero liking for association of two traits in this selection?
NO
YES
226
Regression analysis to find Liking for association of traits
YES
231
Is liking non zero?

FIG. 19

Computing scores for programs for future predictions

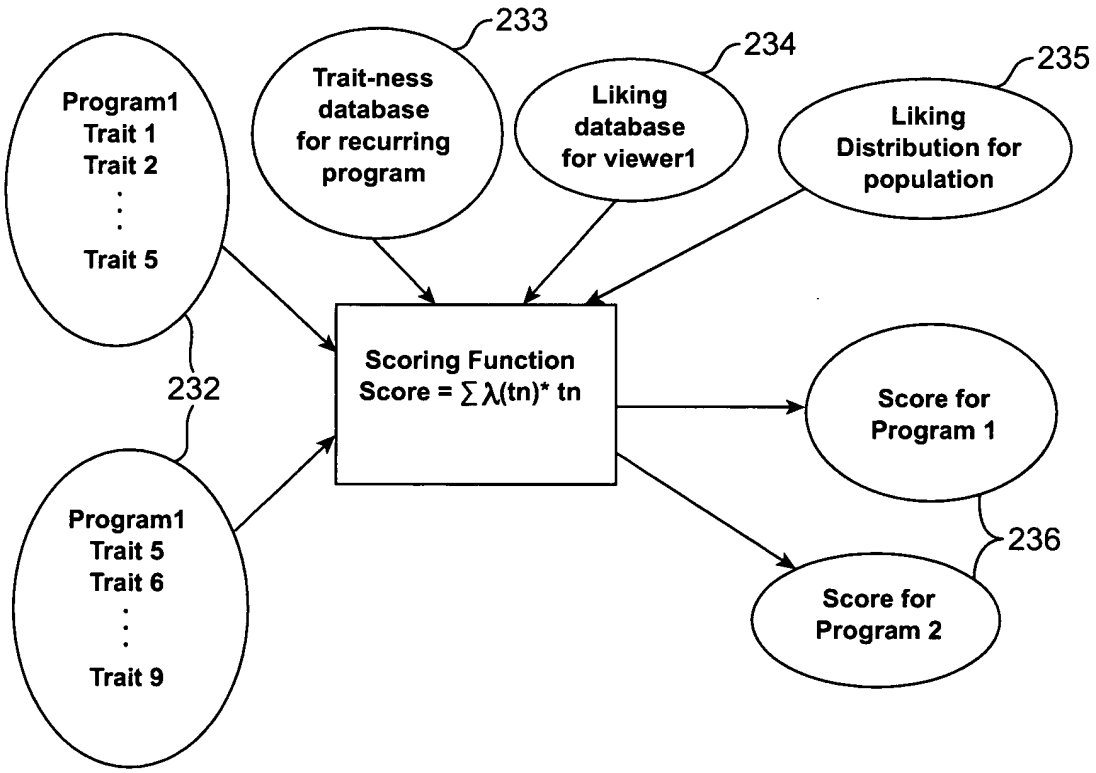


FIG. 20

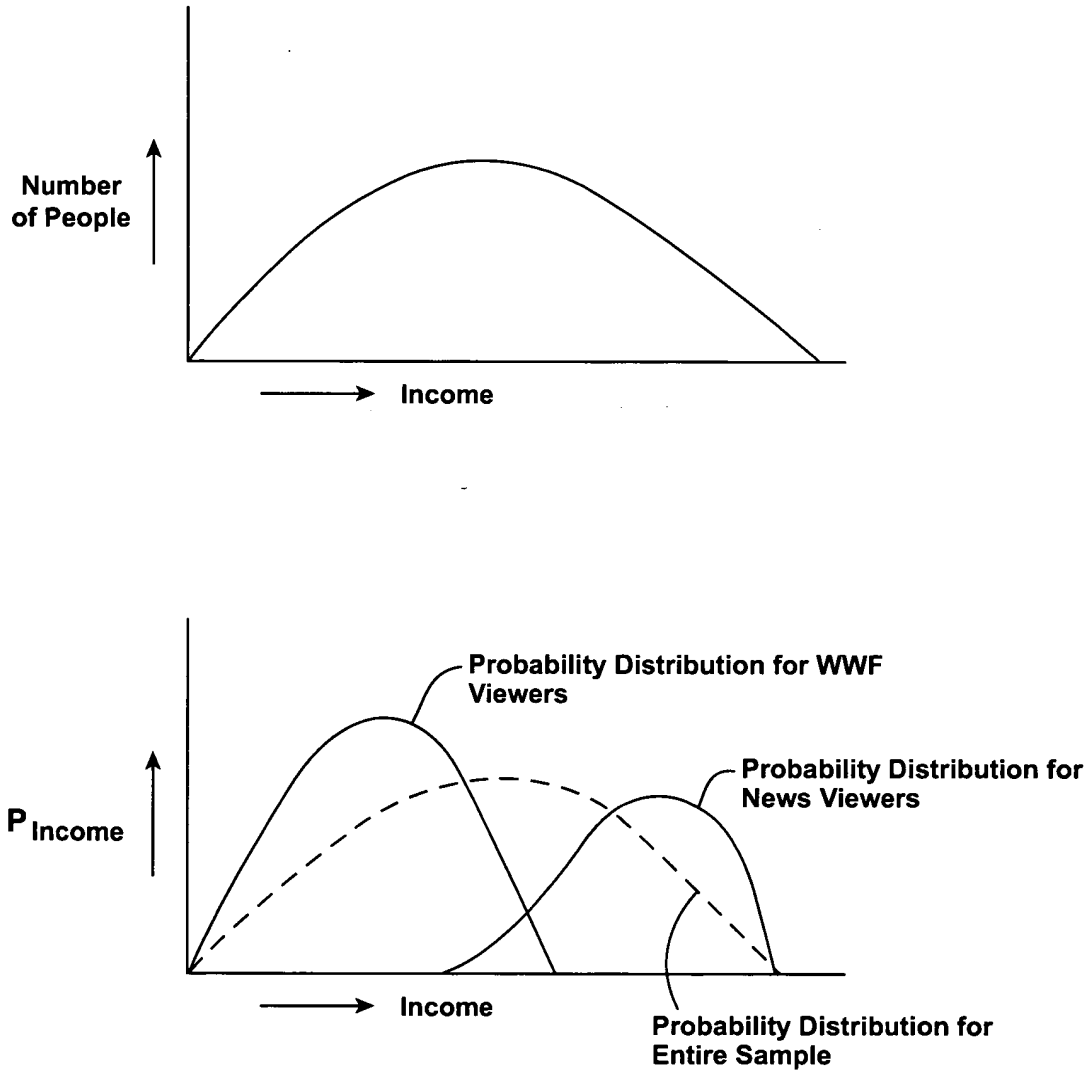

Distribution of Income in Sample
Number of People
Income
P Income
Probability Distribution for WWF Viewers
Probability Distribution for News Viewers
Income
Probability Distribution for Entire Sample

FIG. 21(a)

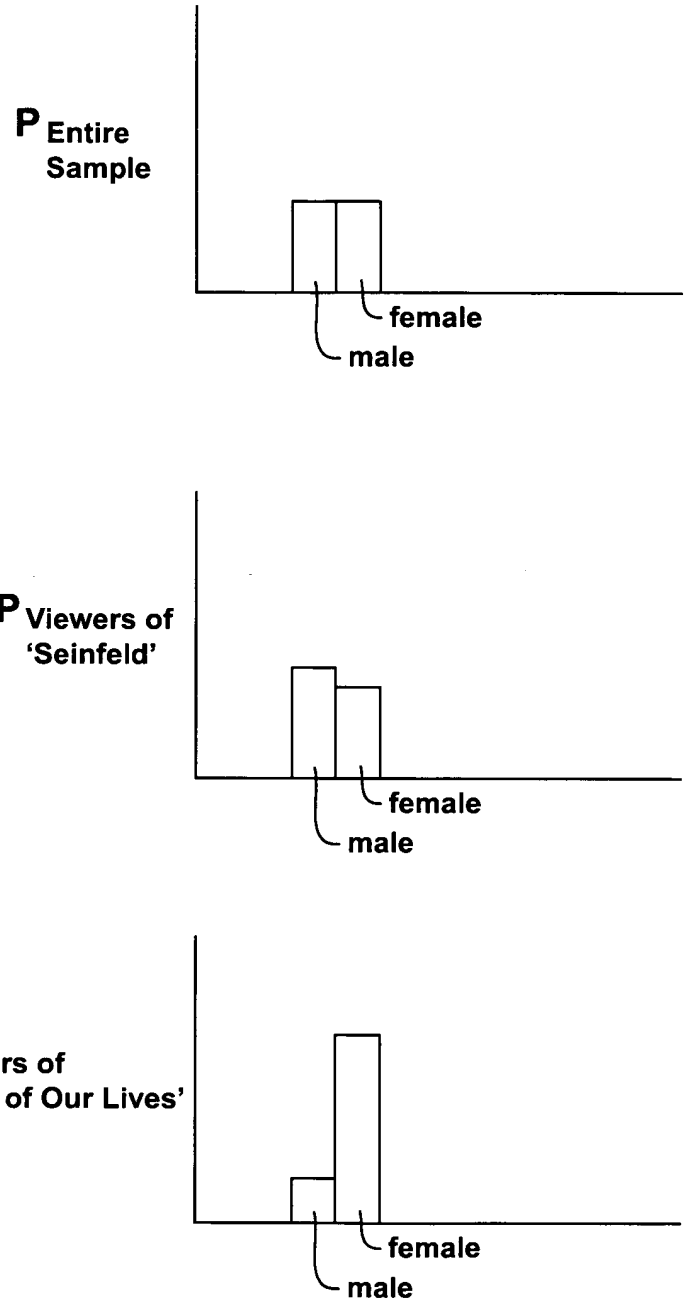

P Entire Sample
female
male
P Viewers of 'Seinfeld'
female
male
P Viewers of 'Days of Our Lives'
female
male

FIG. 21(b)

SYSTEM ARCHITECTURE

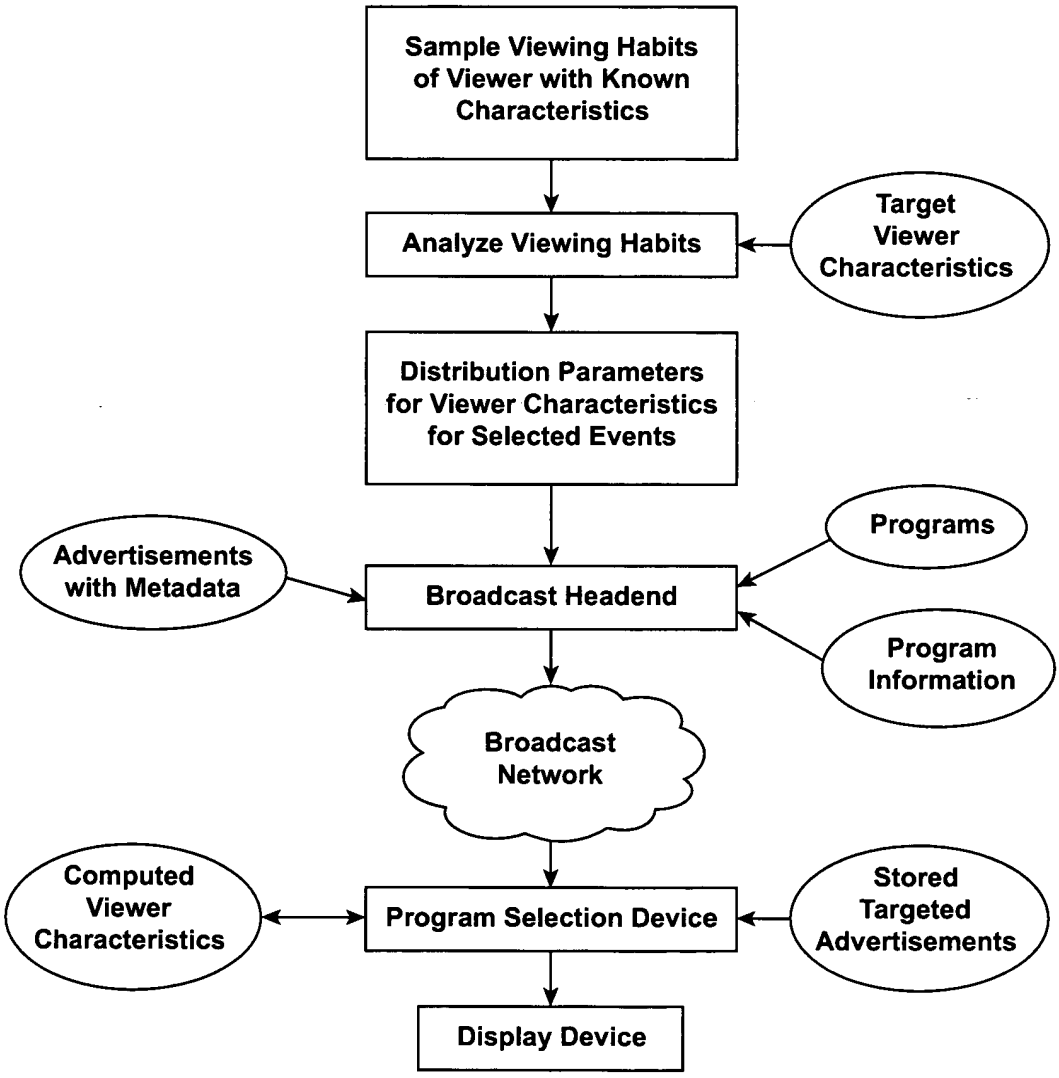


FIG. 22

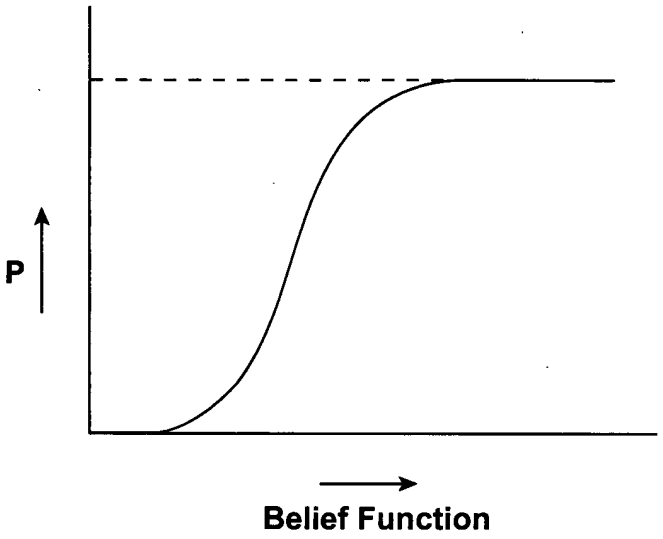


FIG. 23a

Demographic Trait Record format

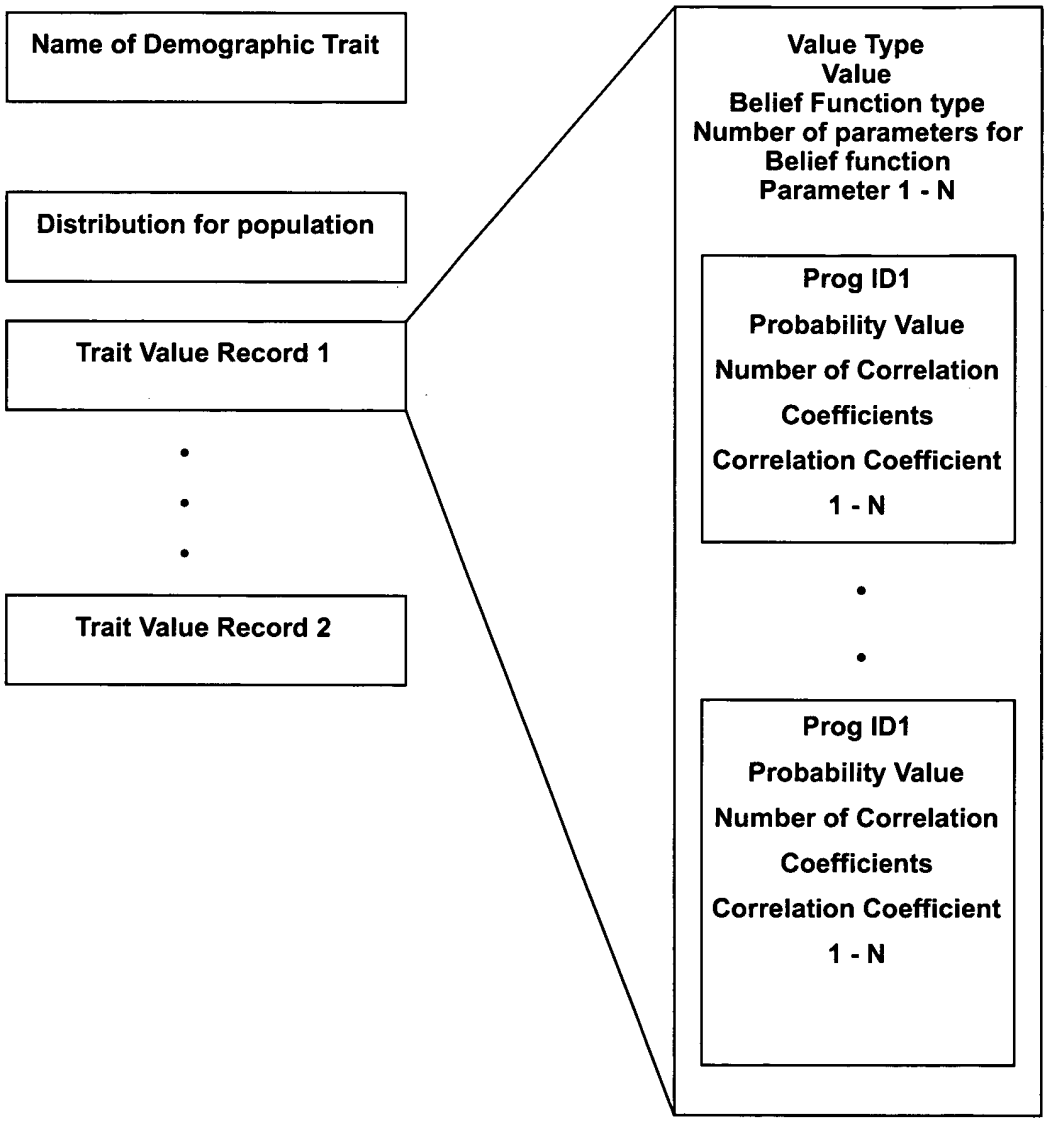


FIG. 23b

Advertisement Targeting Record format

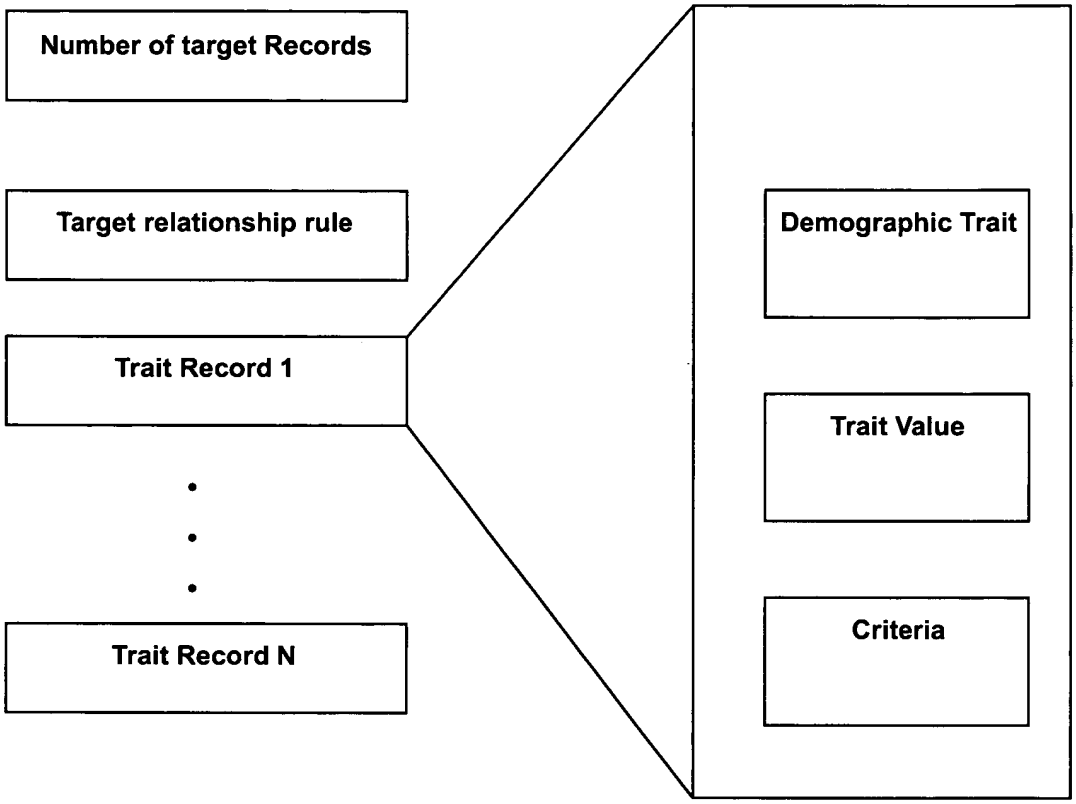


FIG. 23c

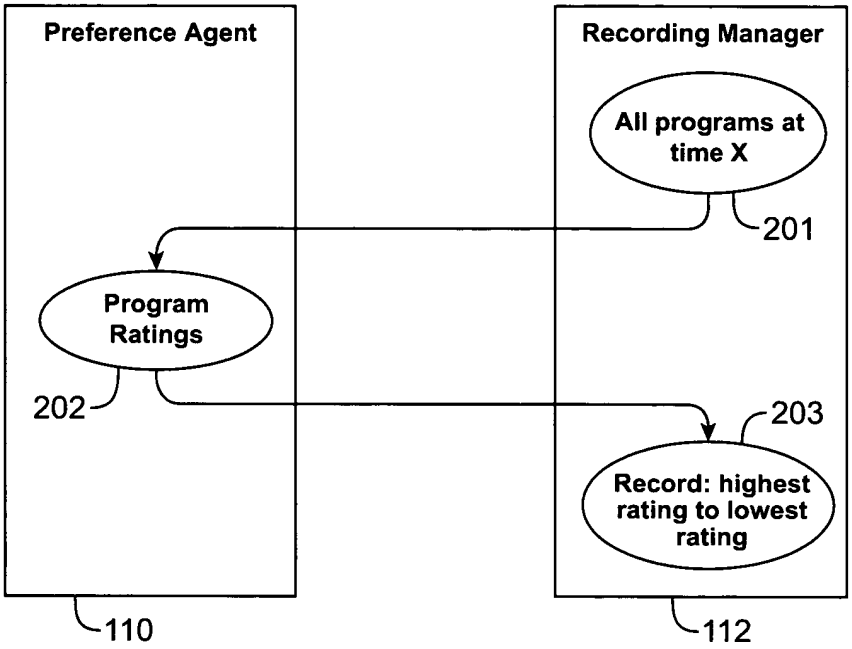

Preference Agent
Recording Manager
All programs at time X
201
Program Ratings
202
203
Record: highest rating to lowest rating
110
112

FIG. 24

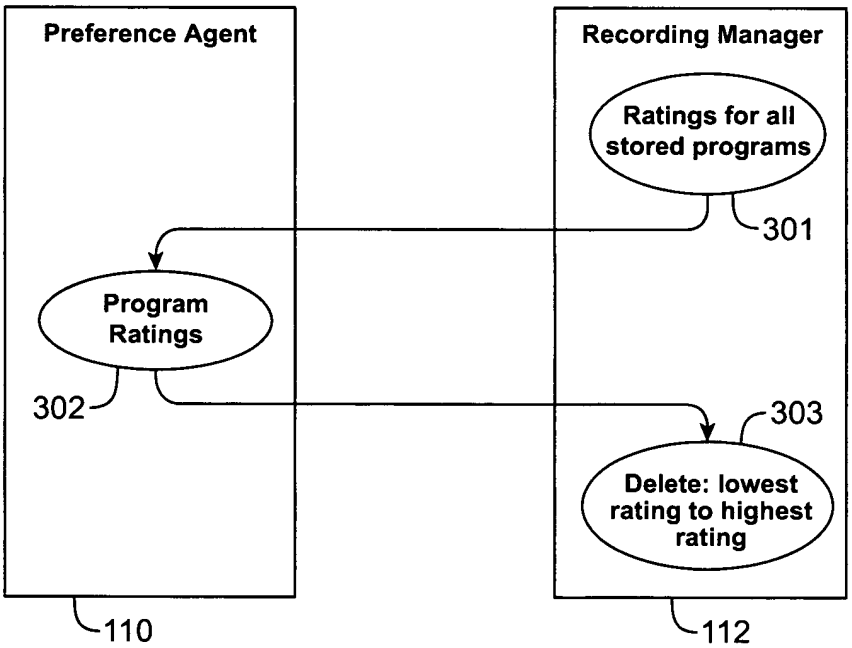

Preference Agent
Recording Manager
Ratings for all stored programs
301
Program Ratings
302
303
Delete: lowest rating to highest rating
110
112

FIG. 25

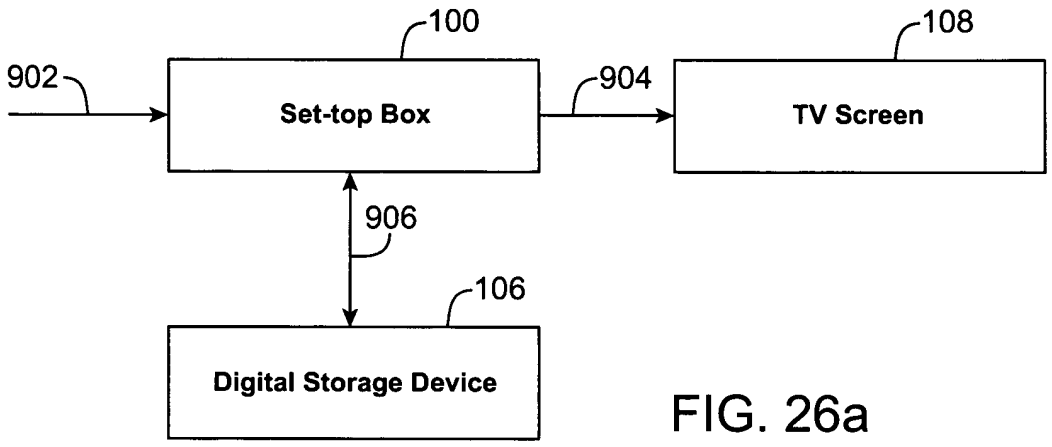


FIG. 26a

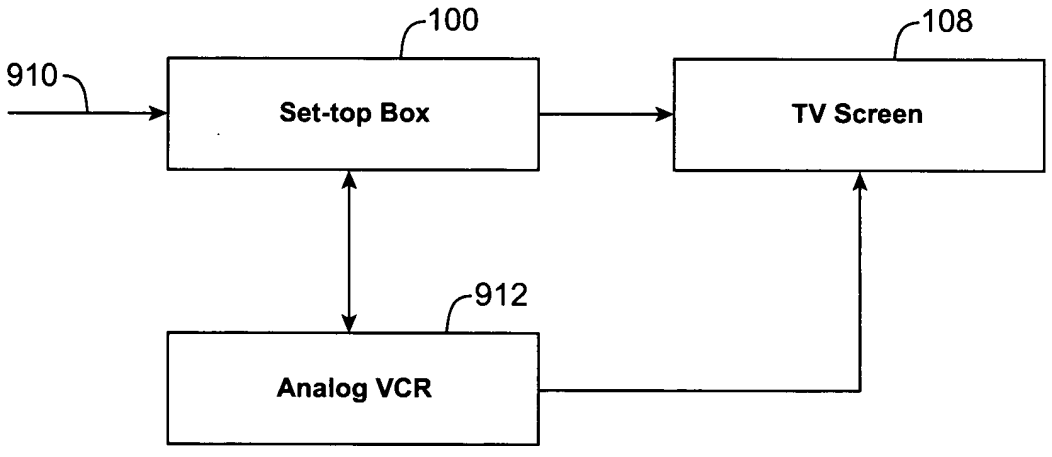


FIG. 26b

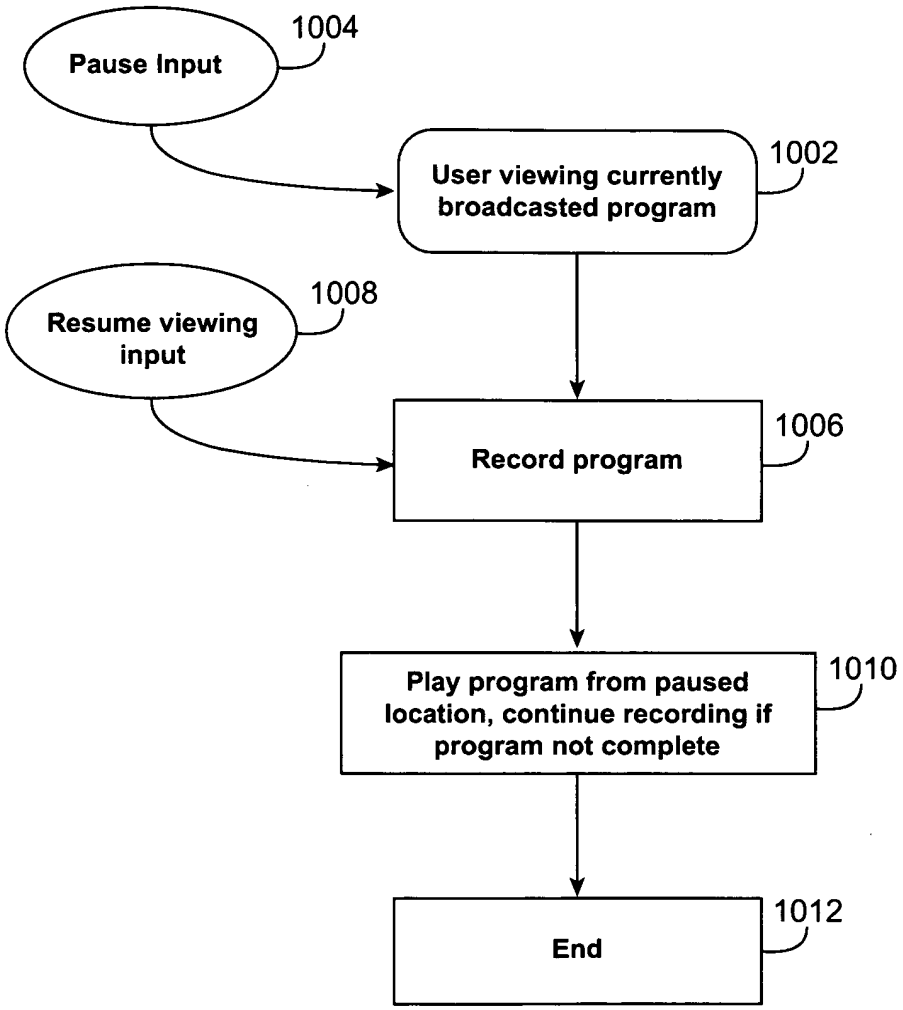

Pause Input
1004
User viewing currently broadcasted program
1002
Resume viewing input
1008
Record program
1006
Play program from paused location, continue recording if program not complete
1010
End
1012

FIG. 27

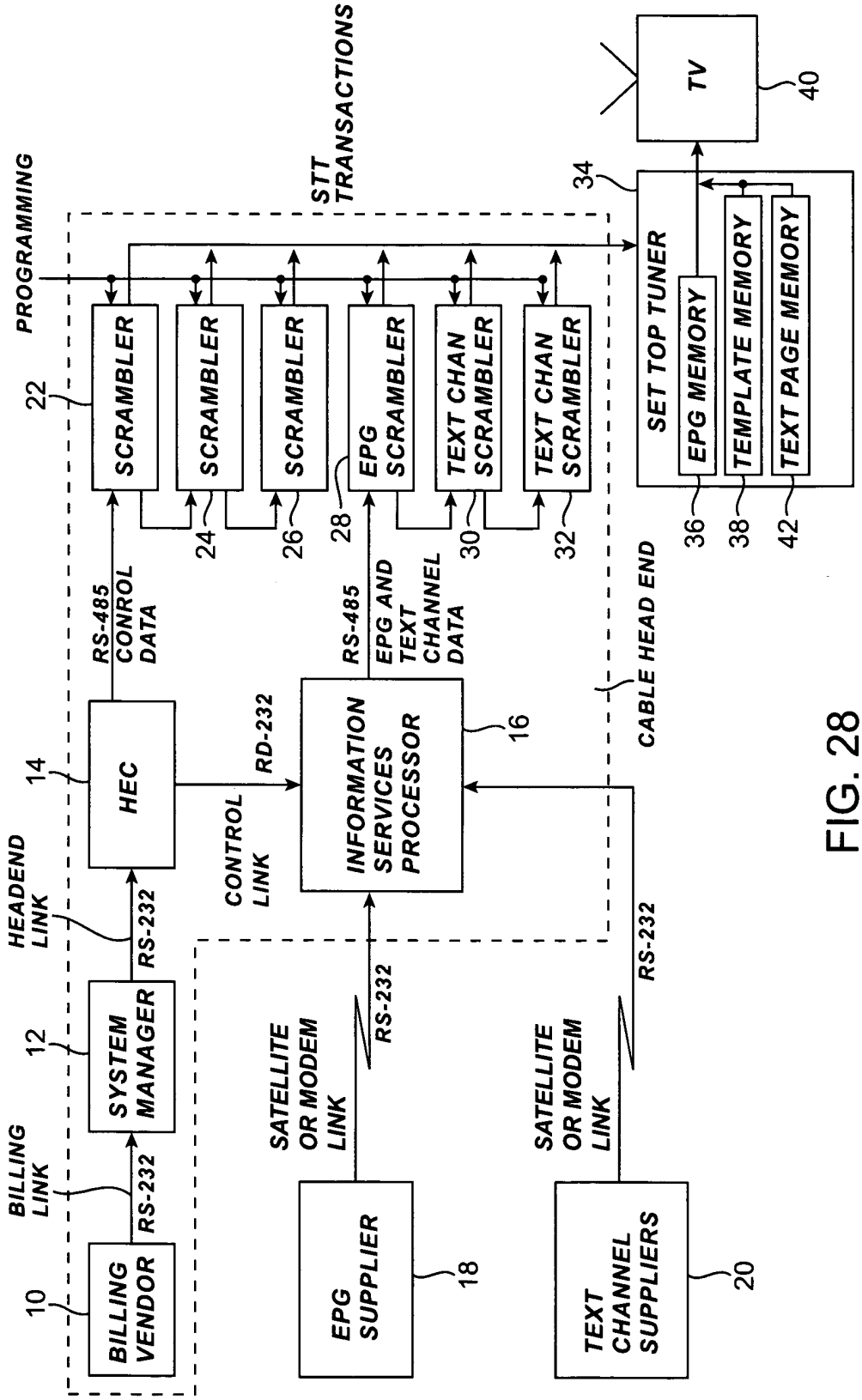

PROGRAMMING
STT TRANSACTIONS
TV
40
34
SET TOP TUNER
EPG MEMORY
TEMPLATE MEMORY
TEXT PAGE MEMORY
36
38
42
22
SCRAMBLER
SCRAMBLER
SCRAMBLER
EPG SCRAMBLER
TEXT CHAN SCRAMBLER
TEXT CHAN SCRAMBLER
24
26
28
30
32
RS-485 CONROL DATA
RS-485 EPG AND TEXT CHANNEL DATA
CABLE HEAD END
HEC
14
RD-232
INFORMATION SERVICES PROCESSOR
16
CONTROL LINK
HEADEND LINK
RS-232
RS-232
SYSTEM MANAGER
12
SATELLITE OR MODEM LINK
RS-232
SATELLITE OR MODEM LINK
RS-232
BILLING LINK
RS-232
BILLING VENDOR
10
EPG SUPPLIER
18
TEXT CHANNEL SUPPLIERS
20

FIG. 28

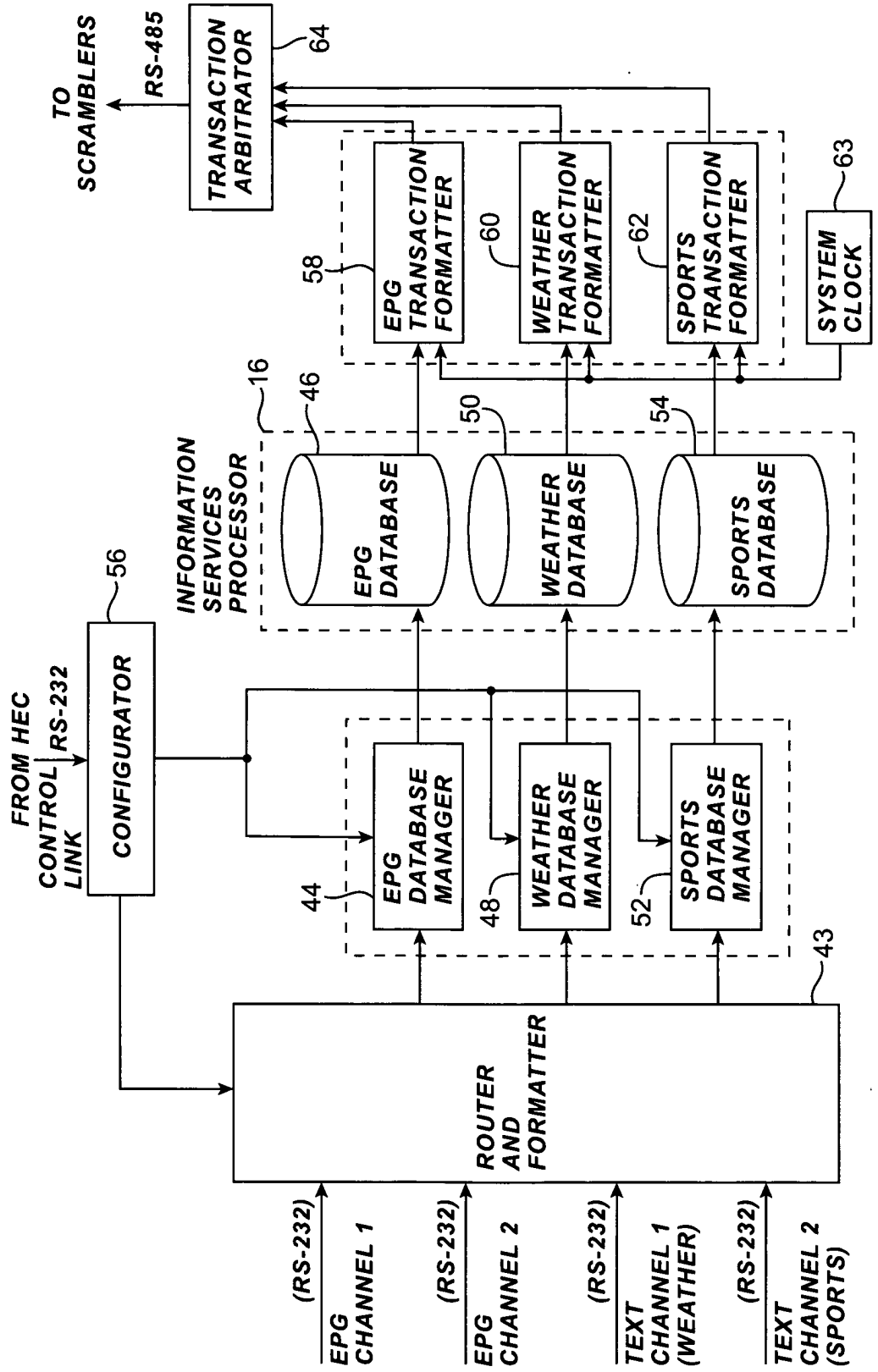

TO SCRAMBLERS
RS-485
TRANSACTION ARBITRATOR
64
EPG TRANSACTION FORMATTER
58
WEATHER TRANSACTION FORMATTER
60
SPORTS TRANSACTION FORMATTER
62
SYSTEM CLOCK
63
INFORMATION SERVICES PROCESSOR
16
EPG DATABASE
46
WEATHER DATABASE
50
SPORTS DATABASE
54
FROM HEC CONTROL LINK
RS-232
CONFIGURATOR
56
EPG DATABASE MANAGER
44
WEATHER DATABASE MANAGER
48
SPORTS DATABASE MANAGER
52
ROUTER AND FORMATTER
43
(RS-232)
EPG CHANNEL 1
(RS-232)
EPG CHANNEL 2
(RS-232)
TEXT CHANNEL 1 (WEATHER)
(RS-232)
TEXT CHANNEL 2 (SPORTS)

FIG. 29

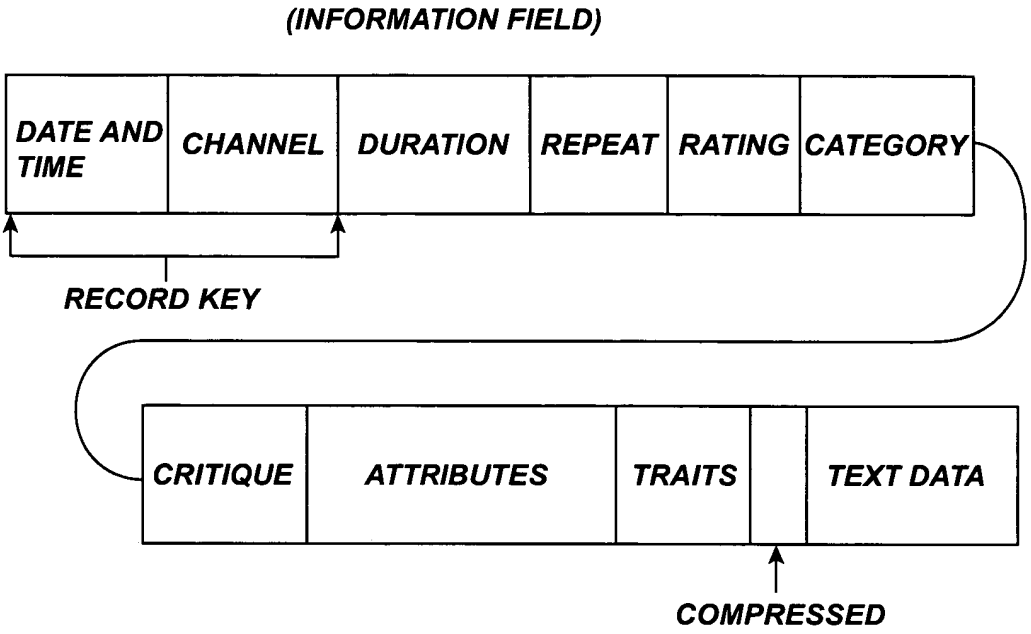

(INFORMATION FIELD)
DATE AND TIME
CHANNEL
DURATION
REPEAT
RATING
CATEGORY
RECORD KEY
CRITIQUE
ATTRIBUTES
TRAITS
TEXT DATA
COMPRESSED

FIG. 30

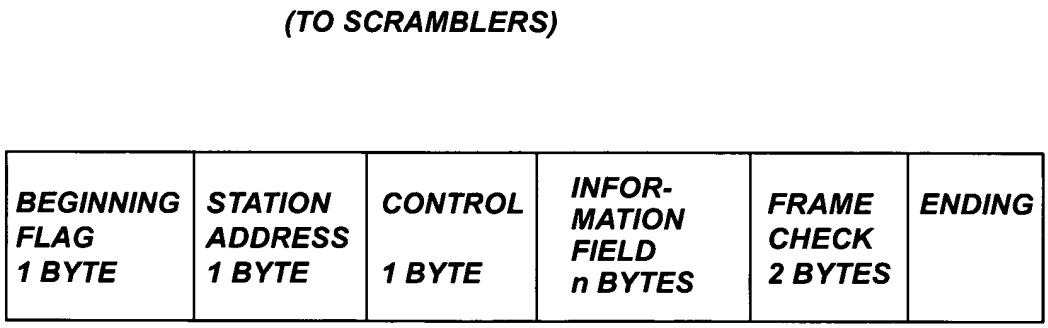

(TO SCRAMBLERS)
BEGINNING FLAG 1 BYTE
STATION ADDRESS 1 BYTE
CONTROL 1 BYTE
INFOR-MATION FIELD n BYTES
FRAME CHECK 2 BYTES
ENDING

FIG. 31

EPG TRANSACTION FORMATTER 58

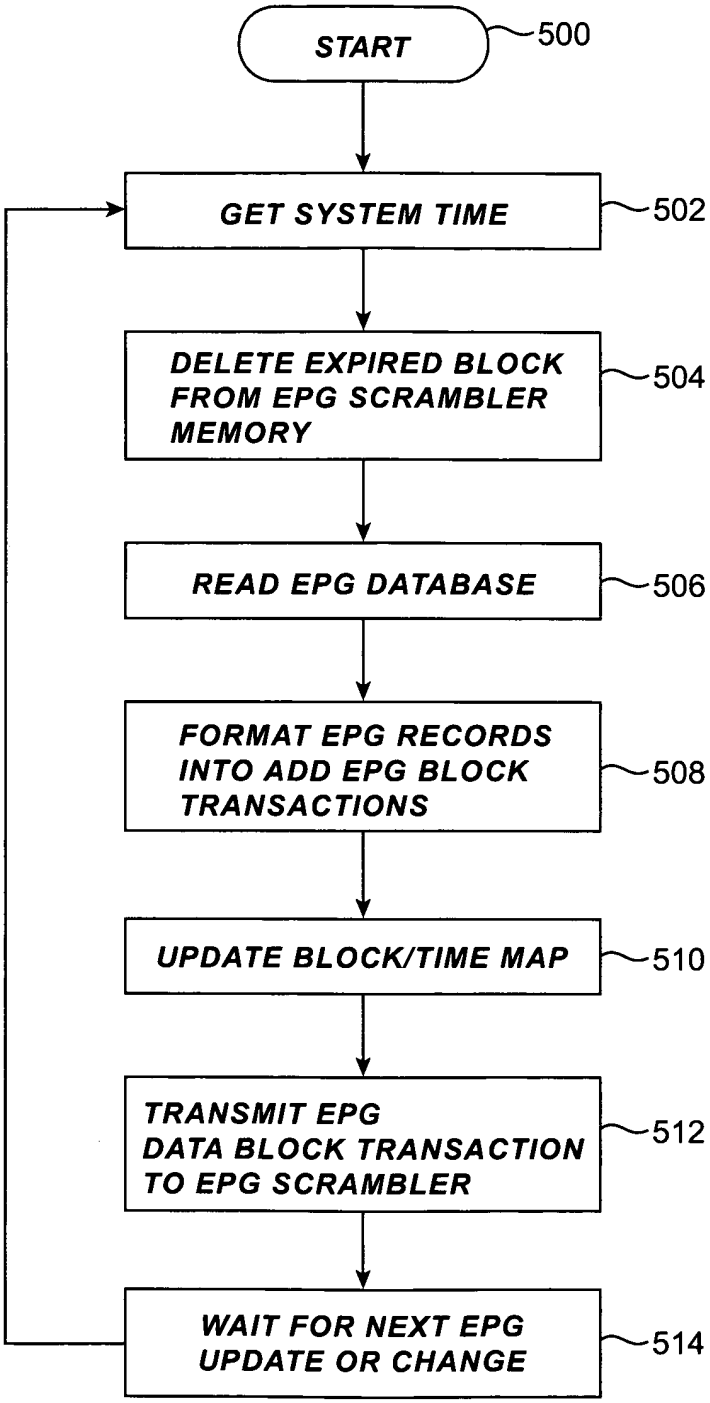


FIG. 32

TEXT CHANNEL TRANSACTION FORMATTER 60,62

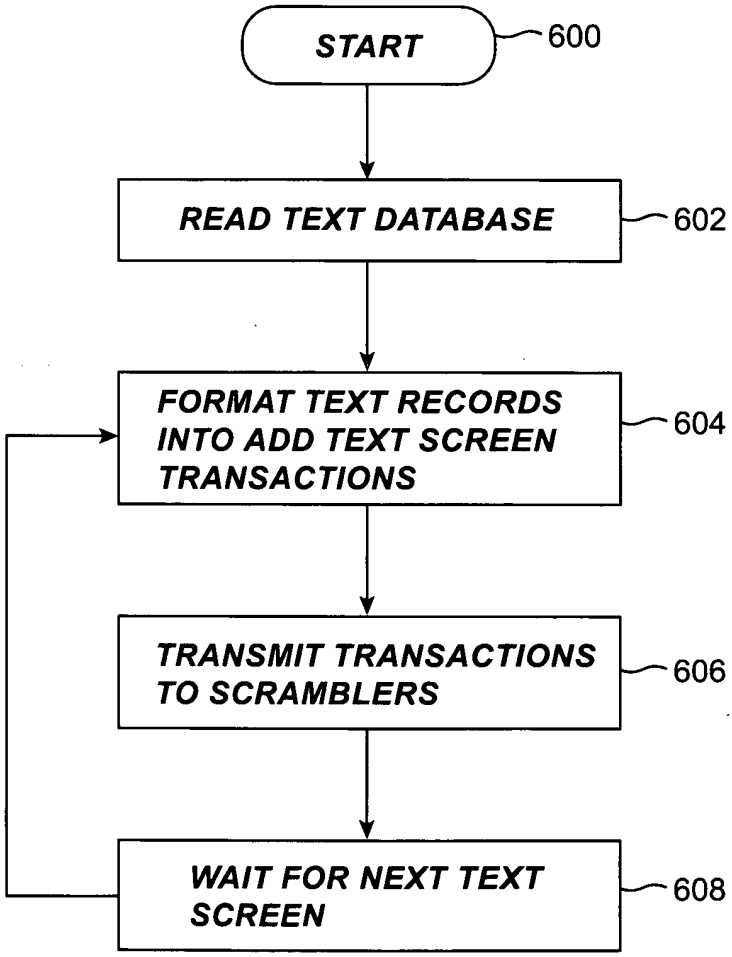


FIG. 33

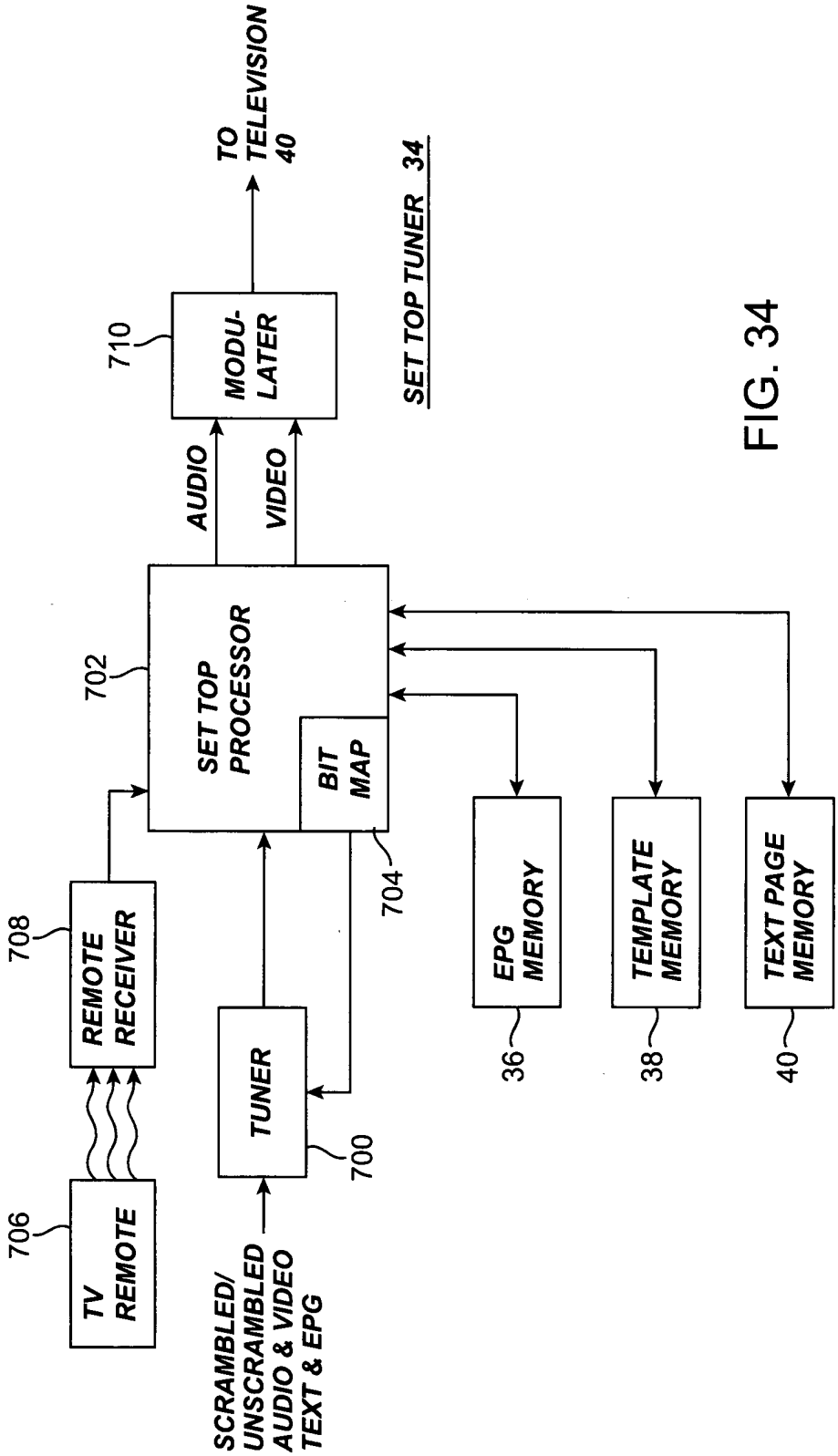

SET TOP TUNER 34
TO TELEVISION 40
710
MODU-LATER
AUDIO
VIDEO
702
SET TOP PROCESSOR
BIT MAP
704
EPG MEMORY
TEMPLATE MEMORY
TEXT PAGE MEMORY
36
38
40
708
REMOTE RECEIVER
TUNER
700
706
TV REMOTE
SCRAMBLED/ UNSCRAMBLED AUDIO & VIDEO TEXT & EPG

FIG. 34

Process for automatically creating multiple profiles and automatically identifying currently active profiles

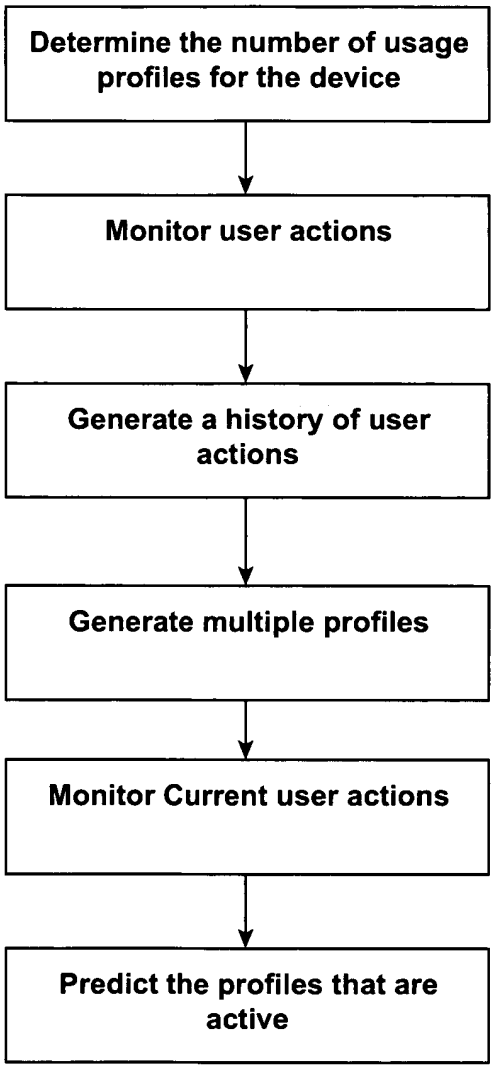


FIG. 35

Process for generating multiple profiles

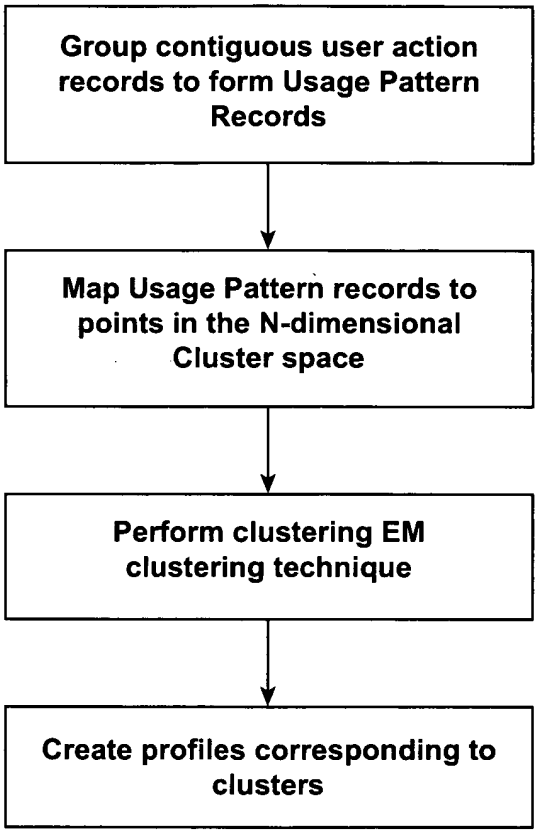
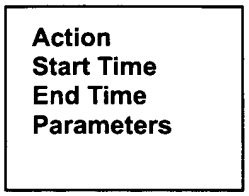
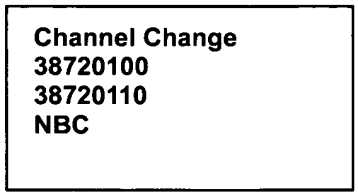


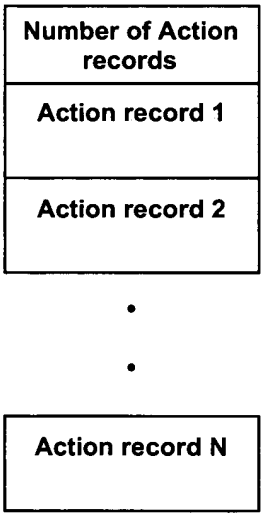
FIG. 36



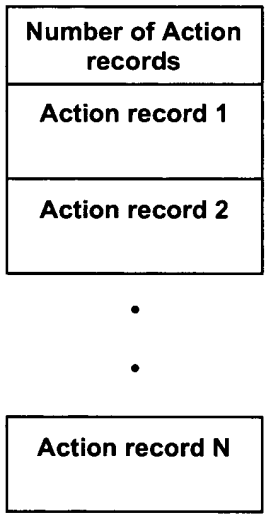
B) Format of user action record



B) Example of user action record

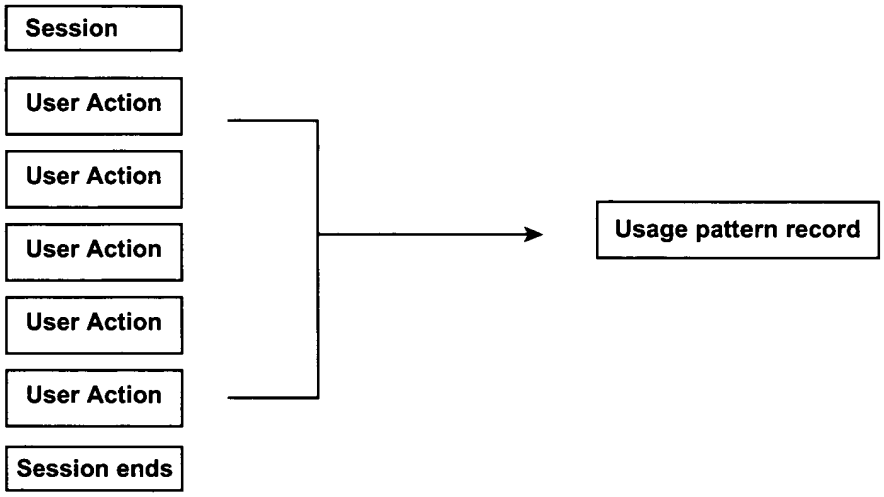


C) Format of History database

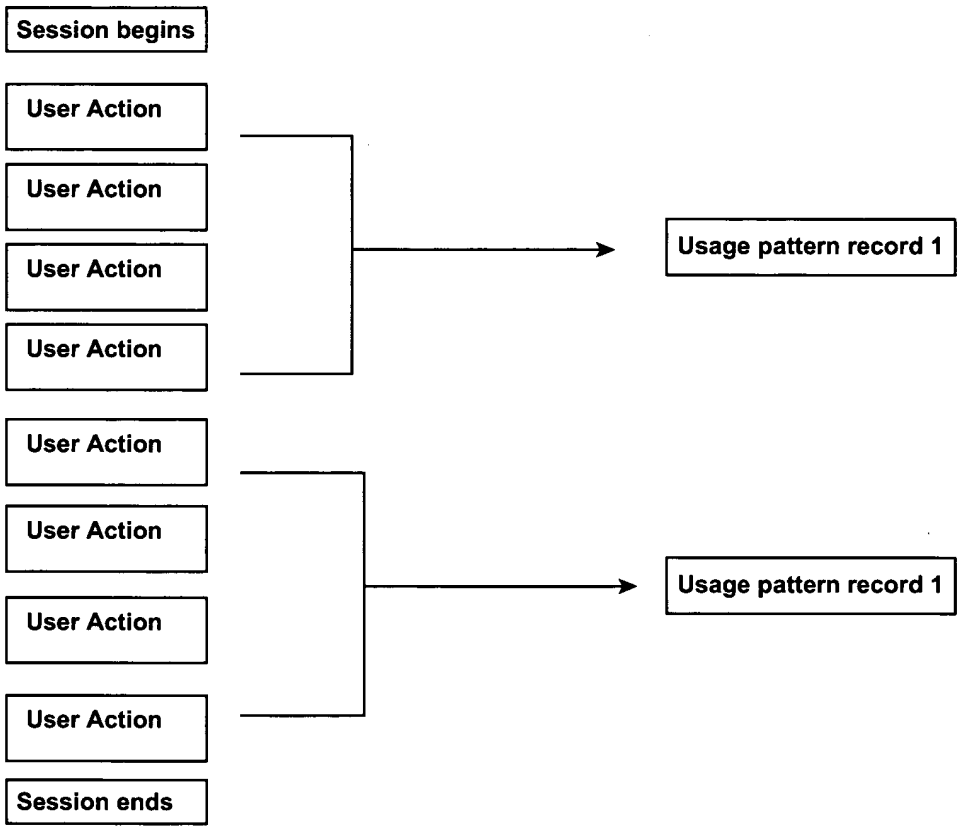


D) Format of Usage pattern record

FIG. 37

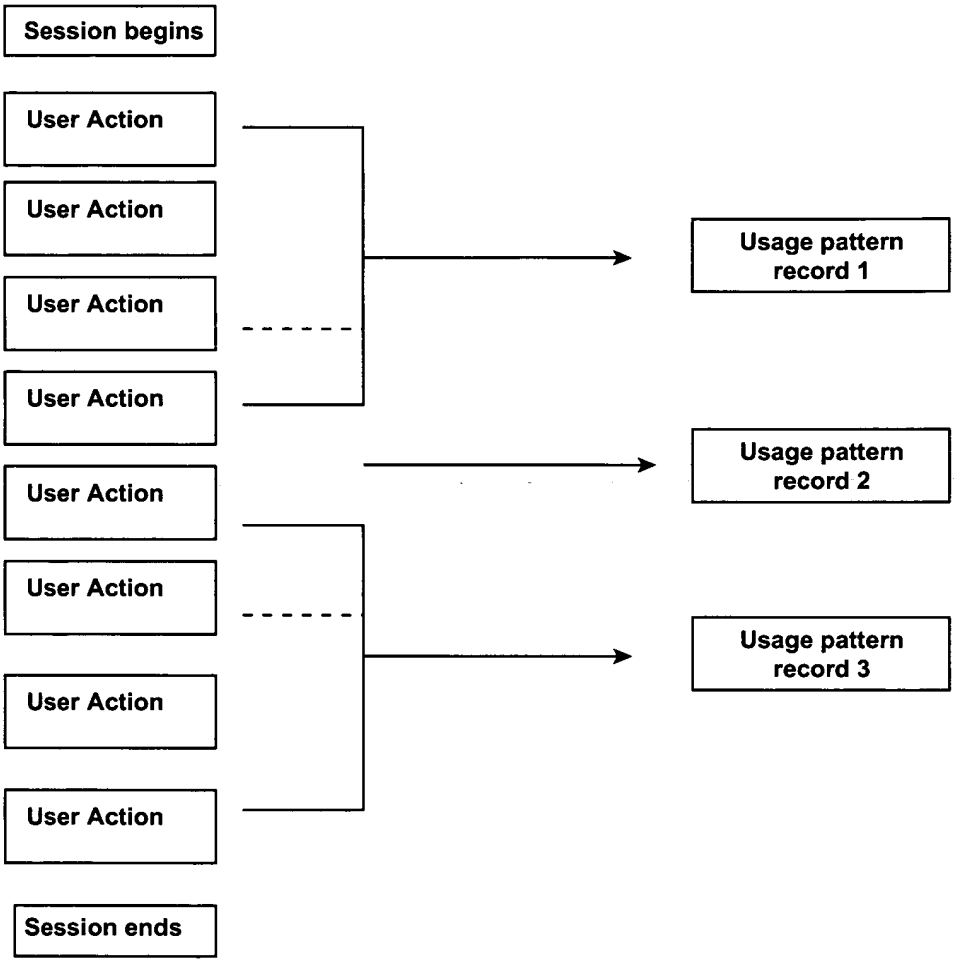


A) One method for creating usage pattern



B) One method for creating usage pattern

FIG. 38



One method for creating usage pattern record

FIG. 39

Process for Predicting currently active profiles

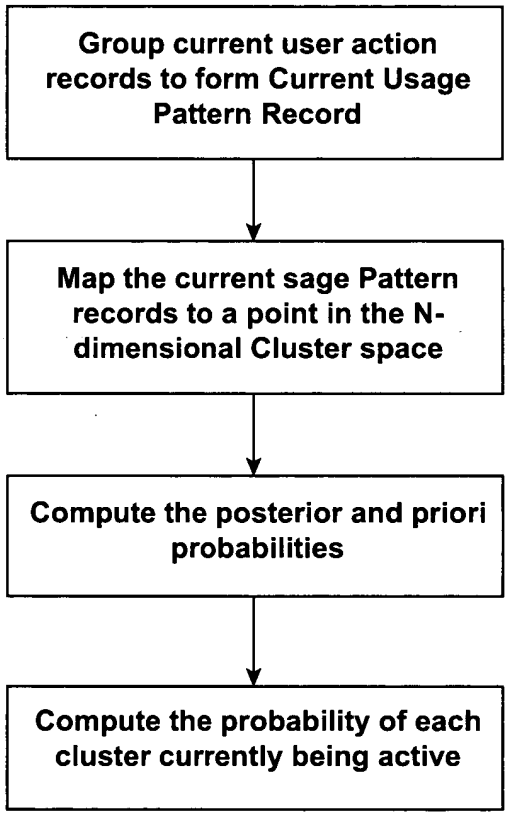


FIG. 40

Profile Creation using Generated Clusters

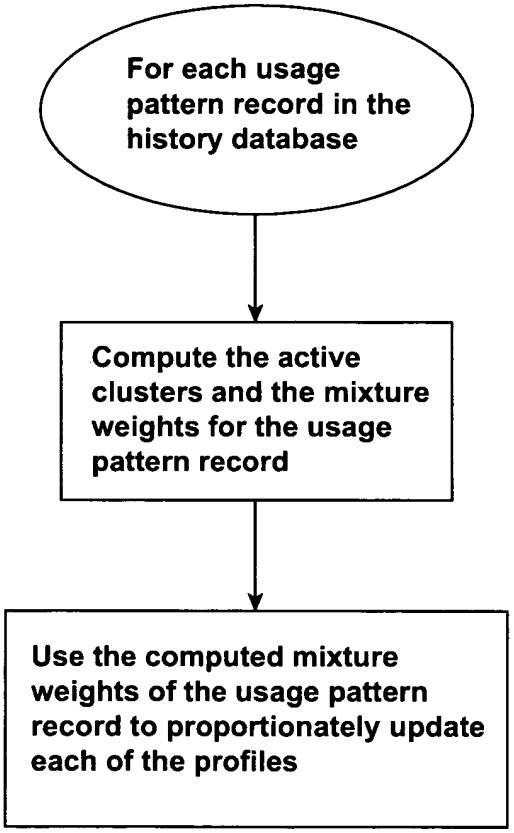


FIG. 41

Targeted Electronic Content Distribution without compromising privacy of users

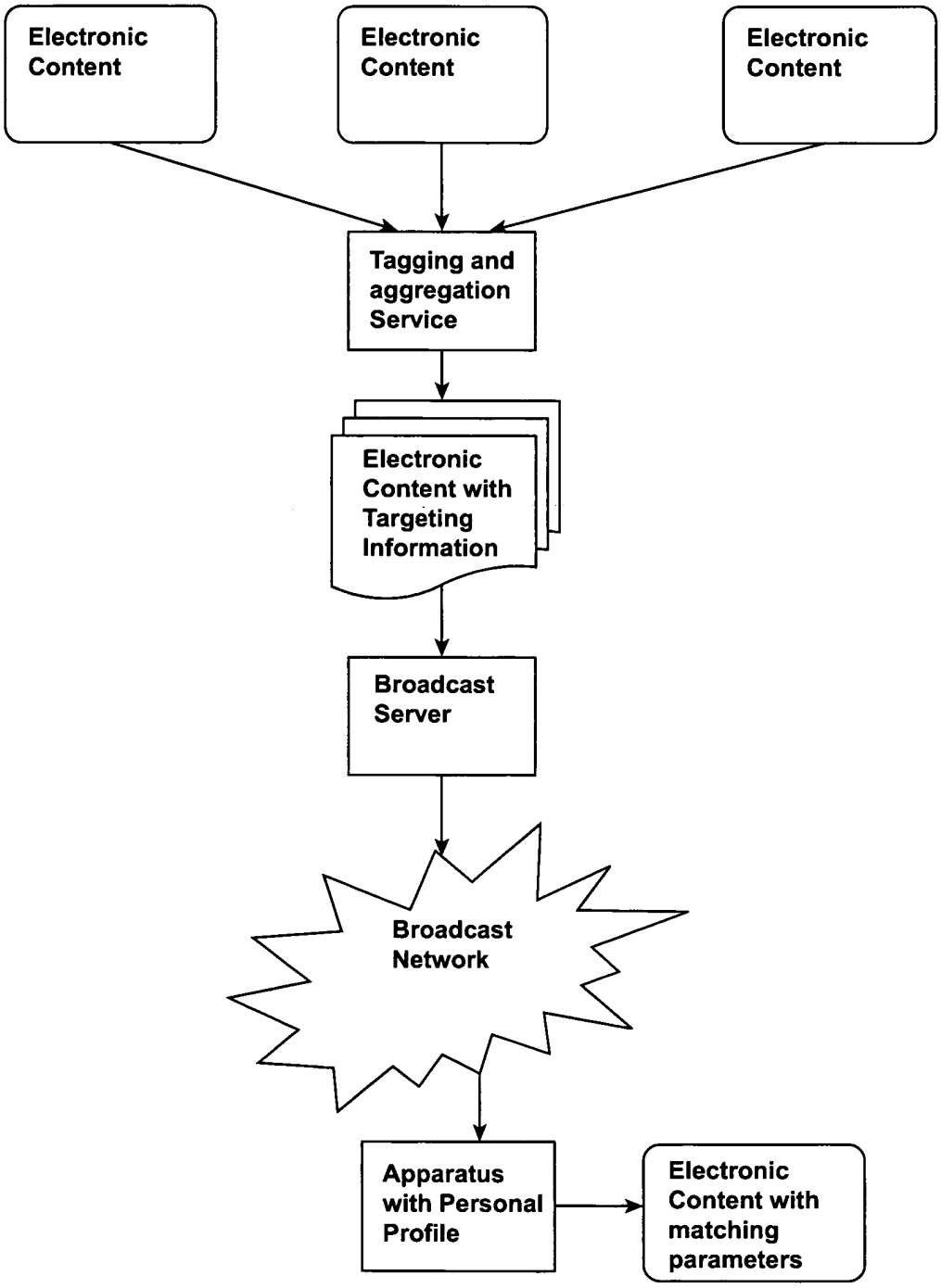


FIG. 42

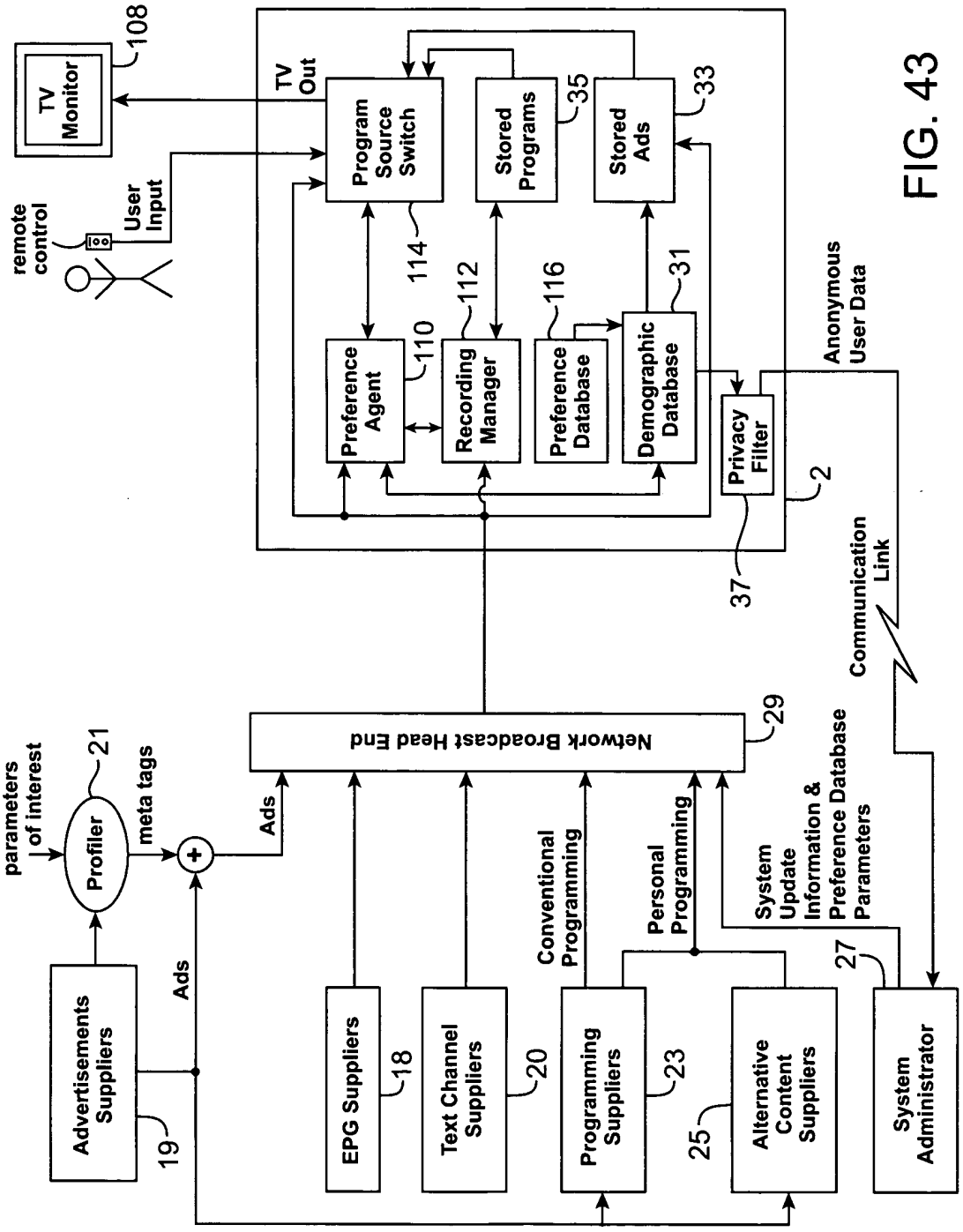

TV Monitor
108
TV Out
Program Source Switch
Stored Programs
35
Stored Ads
33
remote control
User Input
114
112
116
31
Preference Agent
110
Recording Manager
Preference Database
Demographic Database
Privacy Filter
2
37
Anonymous User Data
Communication Link
Network Broadcast Head End
29
parameters of interest
Profiler
21
meta tags
Ads
Ads
Advertisements Suppliers
19
EPG Suppliers
18
Text Channel Suppliers
20
Conventional Programming
Personal Programming
Programming Suppliers
23
25
Alternative Content Suppliers
System Update Information & Preference Database Parameters
27
System Administrator

FIG. 43

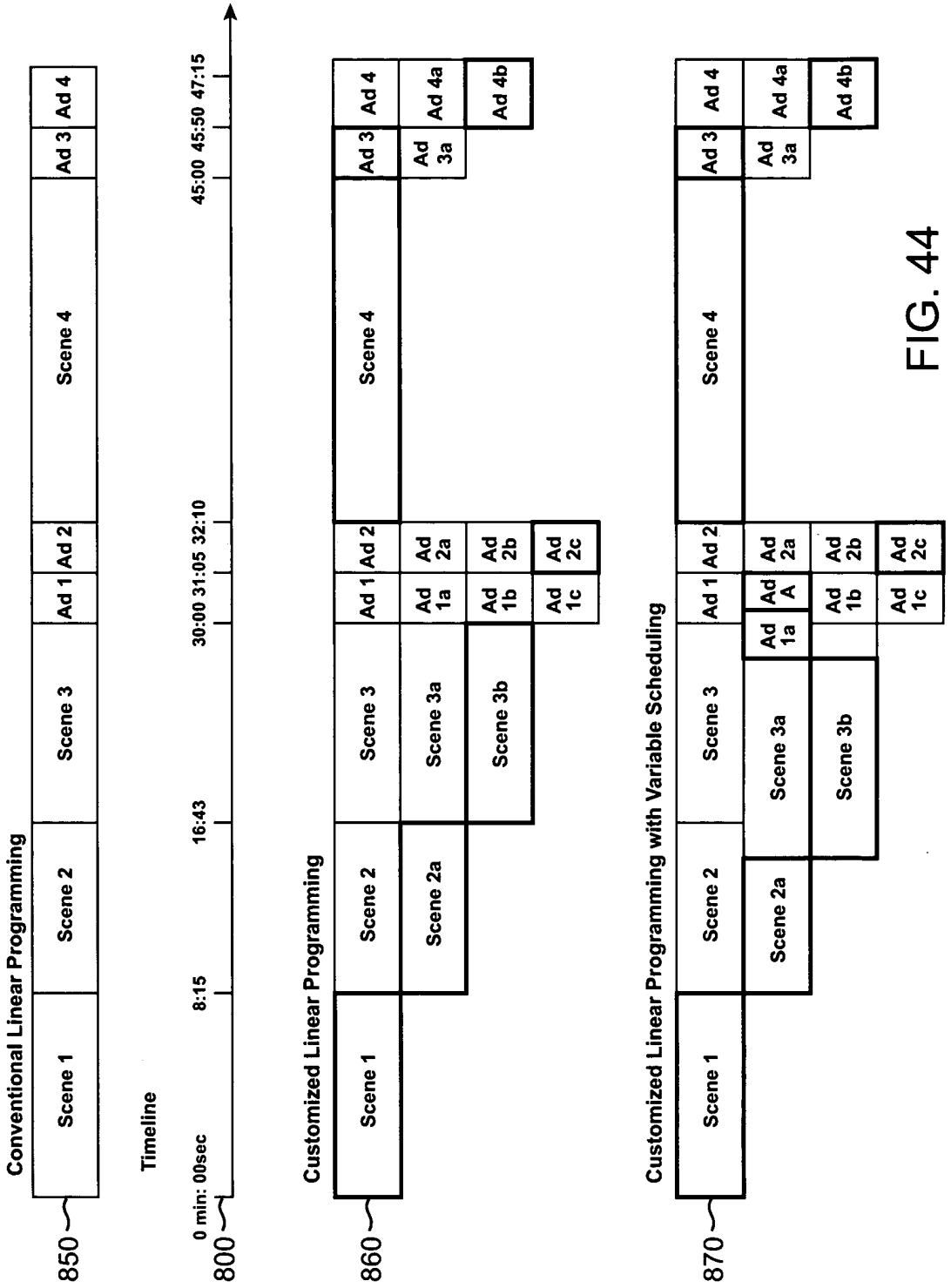

Conventional Linear Programming
Scene 1
Scene 2
Scene 3
Scene 4
Ad 1
Ad 2
Ad 3
Ad 4
850
Timeline
0 min: 00sec
8:15
16:43
30:00
31:05
32:10
45:00
45:50
47:15
800
Customized Linear Programming
Scene 1
Scene 2
Scene 2a
Scene 3
Scene 3a
Scene 3b
Scene 4
Ad 1
Ad 1a
Ad 1b
Ad 1c
Ad 2
Ad 2a
Ad 2b
Ad 2c
Ad 3
Ad 3a
Ad 4
Ad 4a
Ad 4b
860
Customized Linear Programming with Variable Scheduling
Scene 1
Scene 2
Scene 2a
Scene 3
Scene 3a
Scene 3b
Scene 4
Ad 1
Ad 1a
Ad A
Ad 1b
Ad 1c
Ad 2
Ad 2a
Ad 2b
Ad 2c
Ad 3
Ad 3a
Ad 4
Ad 4a
Ad 4b
870

FIG. 44